GEOSPATIAL ESG

THE EMERGING APPLICATION OF GEOSPATIAL DATA FOR GAINING 'ENVIRONMENTAL' INSIGHTS ON THE ASSET, CORPORATE AND SOVEREIGN LEVEL

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SUMMARY

An ongoing challenge with Environmental, Social, and Governance (ESG) efforts is access to robust data. In response, commercial data providers are continually developing solutions to improve insight. Here we discuss one of these potential improvements: the use of geospatial data within ESG focusing on the environmental (E) aspect. Geospatial data can, and is, being used for social (S), and governance (G) purposes, but these are beyond the scope of this paper. This paper explores and tests with real-world examples the potential of geospatial data approaches as means to provide additional insights into the environmental impacts of specific assets, companies, states or nations for sovereign debt investment.

Starting with the current data landscape, the document runs through the open 'environmental' geospatial data portfolio, outlining its strengths and weaknesses. From this vantage point, the report outlines three case studies in Brazil across differing scales, highlighting various key metrics. The first looks at an asset level example, mining operations; secondly a corporate level example looking at soya production (where asset data is unavailable); and finally a national scale example for sovereign debt insights. Throughout the paper, commercial actors provide technical illustrations as to what more would be possible with additional resources.

The document demonstrates that it is possible, even with limited resources and only open data, to generate robust geospatial ESG insights that often can be scaled globally – aiding financial institutions to better differentiate environmental impact at different scales and across different applications. However, as with any method there are limitations. Subsequently, throughout we have tried to illustrate some of the complications which arise with potential outputs, emphasizing the need for actors to carefully consider results in context.

The paper concludes by discussing the various future technical developments, highlighting real-world developments, such as eDNA and machine learning, and their implications for the future of geospatial ESG. Finally, we look at a breakdown of the critical components of geospatial ESG tools, showing where they fall on a spectrum, with most underutilizing the technical toolkit available. As a result of this potential technical growth, combined with greater demand from the financial sector, we expect to see a rapid development of more refined geospatial ESG products and insights in the near future.

KEY POINTS:

- Geospatial ESG is emerging into the mainstream, and as yet, there are no universal frameworks or metrics for defining the environmental impact (and dependencies) of various asset classes.

- Robust insights are already possible for some sectors, limited primarily by the extent and availability of asset data (which define location and ownership of assets) and supply chain data.
  - Asset level to corporate level screening has been achieved for sectors such as oil and gas, mining, fishing, shipping, cement, steel and the power sector. Indeed, commercial factors such as Asset Resolution, Verisk Maplecroft, Reprisk, Bloomberg and others already offer geospatial ESG-derived data products. Some, such as the Trase tool, even manage to generate insights from incomplete asset data, providing estimates of a company's supply chain deforestation risk.

- Geospatial ESG methods are scalable, across both number of assets and sectors; in this paper we generate insights for mining assets in Brazil which could be applied globally:
  - Defining the high-level impact of mines; considering impact to habitats, conservation areas (considering the intactness and importance variance of each individual conservation area), freshwater exposure, etc.
  - Ongoing monitoring, land degradation, emissions, tailing dam growth and volumetric expansion of the mines.
  - Defining an 'environmental ratio efficiency' of mines (or aggregating to the corporate level) against local or global peers, where the weighted extent of habitat destroyed (and other key environmental costs) is considered against mining production year on year (and any other major positive values).

- The open data portfolio has limitations. However, data is improving year on year, with major intergovernmental initiatives pushing to significantly improve the 'environmentally relevant' data portfolio for initiatives such as the UN's Sustainable Development Goals (SDGs).
  - One important tension in the future of geospatial environmental insights is the role of the international governmental agencies (IGOs) and the non-governmental organizations (NGOs) in data provision. Often these agencies are uniquely placed to deliver environmental datasets yet may choose to restrict access to their data for commercial application or may lack the means to be able to generate data products at the required frequency or detail. The private sector will continue to fill data gaps; however it is likely to remain with the IGOs and NGO to provide data in some specific areas. Consequently, a question mark remains over the role, responsibilities, funding and ethics of the IGOs and NGOs in gatekeeping critical environmental data.

- Future data developments, such as using machine learning to update multiple observational data layers from one high resolution land cover layer, improvements in ground species monitoring and habitat disturbance detection, are likely to play an important role in providing improved insight.
  - Significantly our understanding of threats, impacts and the health of ecosystems at scale are likely to dramatically improve with new ground sampling methods, such as eDNA, and landscape audio, with complex machine learning models amalgamating these new species of ground data insights with other geospatial data, i.e. climate, geographic and land cover data.

- It is increasingly evident that tailored sector and site specific geospatial ESG methods and metrics are required to maximize insight. However, such sector specificity creates potential difficulties when attempting to integrate different sector specific metrics at the portfolio level. Adding to these aggregation challenges are the differing needs of users, such as portfolio analytics for equity investment versus tailored site-specific investigations for project finance.

- The majority of open and commercial geospatial ESG platforms do not yet fully utilize all the data and technical methods available (see diagram below), creating the potential for rapid development. Yet, the immaturity of the data marketplace for asset, supply chain and observational data is likely at least in the short term to act as a constraint in some areas.

COMPLEXITY

ASSET DATA

Asset location

+ Sector specific attributes
E.G. power plant, real estate, farm - cotton.

+ Site specific attributes
E.G. hydro power plant reservoir size, power production Mw.

+ Additional external data
E.G. web scraped data.

+ Supply chain asset data
The asset data of all major or significant suppliers and their suppliers.

+ Other data
Traditional ESG data points, economic, social data points, ground data etc.

OBSERVATION DATA

Single layer
One vector layer or raster layer included in analysis.

+ Multiple layers
Two or more vector layers or raster layers included in analysis.

+ Dynamic data
Near real-time feed of data, weather data.

+ Sector specific monitoring data
i.e. methane detection, marine oil spill detection, night time flaring, for oil and gas assets.

+ Historic and future data
E.G. past temperature averages, extreme weather events.

+ Other data
E.G. social, economic, governance data points, ground data, etc.

DATA PROCESSING

Direct comparison
Asset overlaid by one or multiple observational data layers.

+ Sector and site specific weightings
Impact adjusted to sector and site variables

+ Observational inferences
Refining, backfilling observational data from other variables.

+ Interdependence
The site specific impacts considering the interdependencies of natural assets, e.g. forest loss impacts on wider local water security.

+ Near real time adjustment
Results updated frequently and capable of adjusting to near real time data feeds, e.g. oil spill.

AI

+ Machine rationalization
Analysis is adjusted to the best regional data and regional models based on dynamic machine rationalisation of the options present.

+ Machine learning
Throughout any of the various data sourcing, data processing or results, machine learning is applied to iteratively improve outputs.

INTRODUCTION

For decades, the financial sector has incorporated geospatial data to better understand opportunities and risks, whether non-material or financially relevant. The insurance industry, for example, has long used complex geospatial models for catastrophe management, such as determining the risk of extreme weather to real estate, and are now arguably at the leading edge of modelling how extreme weather events are likely to change under different climate scenarios. In recent years there has been an uptick in interest around the application of geospatial data to support Environmental (E), Social (S), and Corporate Governance (G) (ESG) insights.[1]

'Geospatial ESG',[2] is defined here as the use of geospatial data to generate ESG relevant insights into a specific commercial asset, company, portfolio or geographic area. Geospatial ESG begins with the accurate location and definition of ownership of a commercial asset (e.g. factory, mine, field, retail estate), known as 'asset data'. Then using different geospatial data approaches it is possible to assess the asset against 'observational data', to provide insights into initial and ongoing environmental impact and other social and governance variables. Geospatial data can be integrated with ground monitoring data (e.g. smart meters, eDNA) and traditional ESG data points for even greater insights. The advantage is clear: an additional data source, capable of providing independent, global, high frequency insights into the environmental impact and risks[3] of single assets or companies (by grouping the assets of a company and its supply chain), or within a given area such as a state or country.

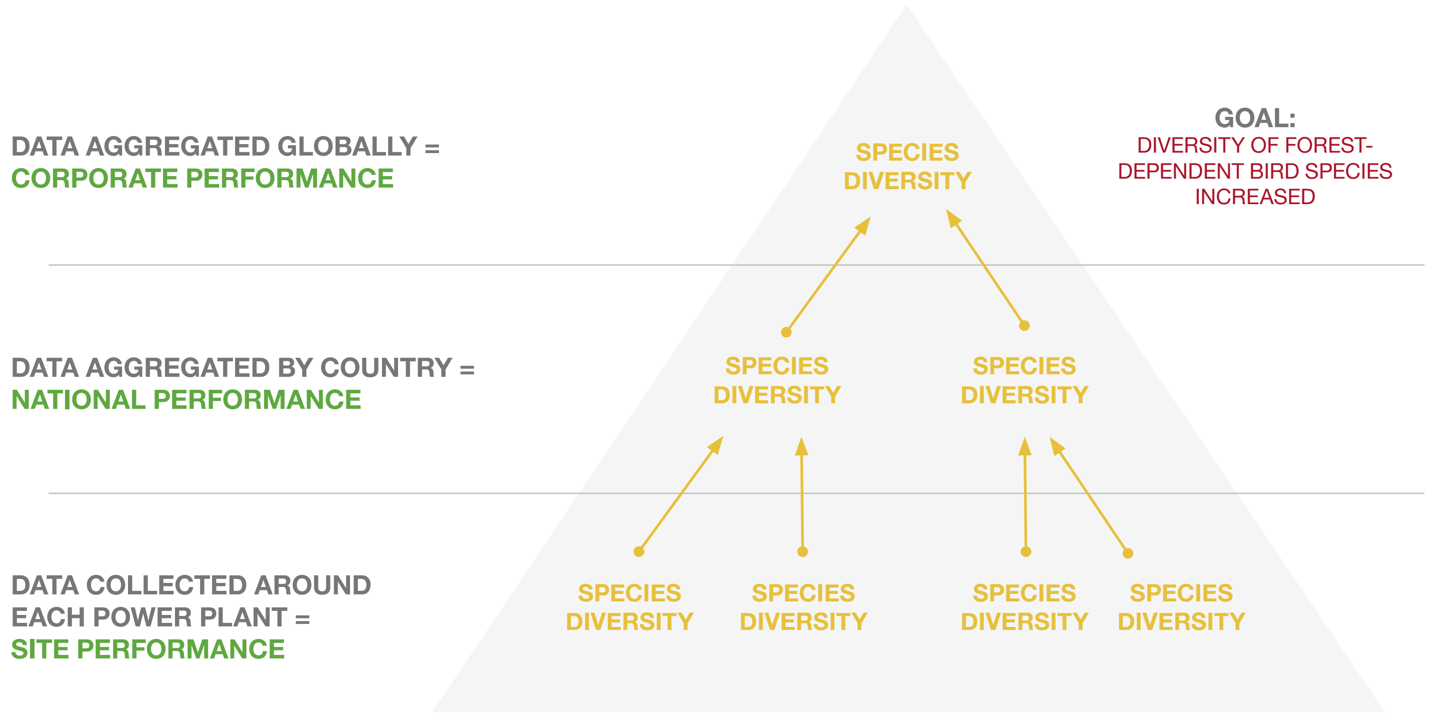
This rising interest, to determine environmental risk and financial materiality, coincides with improvements in satellite technology and machine learning, spurring the development of an energetic world of related start-ups offering niche or more general data services, such as marine oil spill detection,[4] wildfire prediction,[5] methane emission detection,[6] carbon emission prediction from the heat profile of factories[7] or exposure to deforestation within supply chains.[8] This arrives at a time when pressures on financial institutions (FIs) are increasing on three major fronts: 1) growing calls for voluntary and increasingly mandatory disclosure (e.g., TCFD[9]) and regulation (e.g. launch of EU Taxonomy and SFDR; UK Green Taxonomy); 2) the need to address 'double materiality' (e.g., in TNFD[10] scope), which recognizes not only the financial materiality to companies arising from ESG risks and opportunities (dependencies) but also the materiality for society and the environment arising from the companies' operations (impacts), which in turn can result in financial risks; and 3) the growing importance around the topic of the 'environment'.[11] Recognizing the increasing attention and opportunities, over the last few years, the larger business intelligence providers have increasingly begun integrating various 'environmental' geospatial data points into their ESG products. Alongside this mainstreaming, some financial institutions have begun to expand their technical capacities to make use of geospatial data in-house, often with an initial focus on climate change.

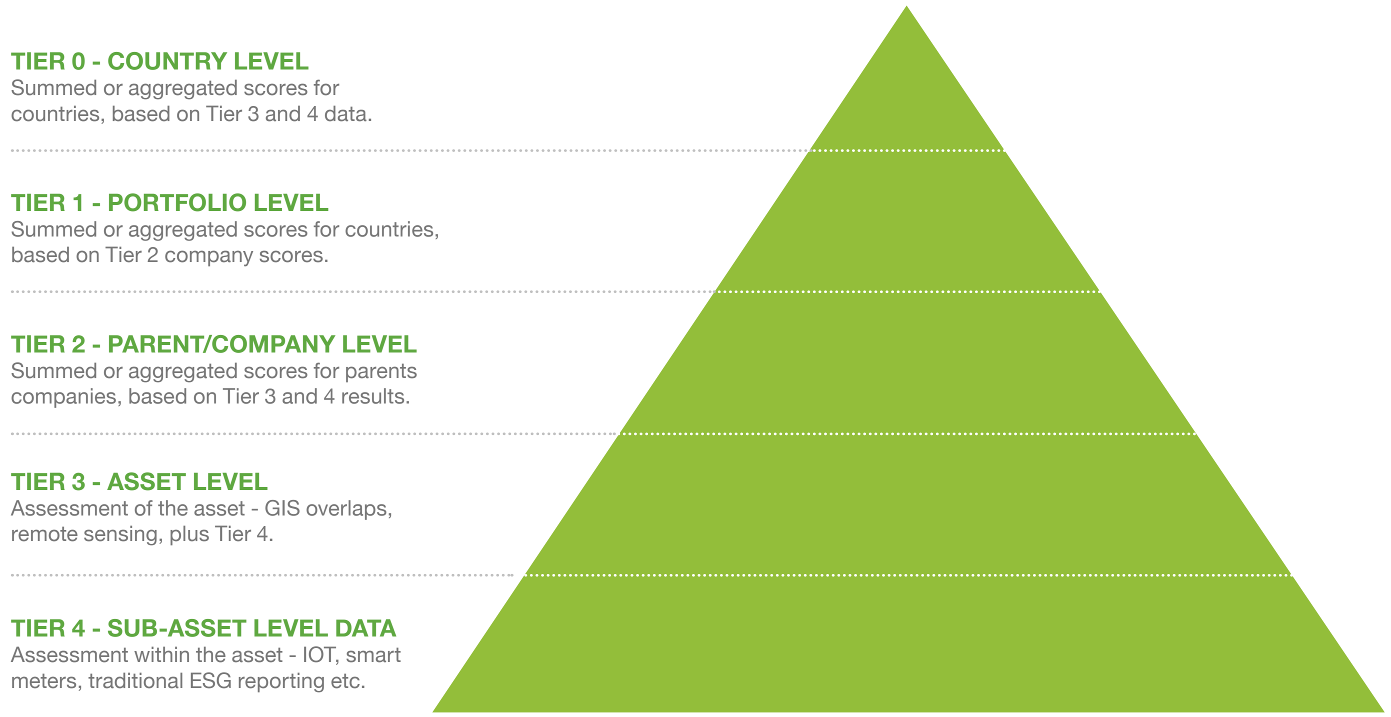
Unfortunately, the complexity of natural systems and the diversity of commercial operations have made it difficult to develop clear metrics to define environmental impact and dependencies. Generating robust insights – across diverse commercial operations each with a differing impact; across vastly different natural habitats with differing sensitivities; and combining complex global supply chains each with differing impacts and dependencies – has proven problematic. The situation is further hampered by a lack of data availability at a high granularity at a sub-national level, where data simply may not exist for key variables and with no disclosure required in most cases. Combined, these issues have compounded to make measuring environmental impact at the company scale and above extremely challenging.

Prior attempts to resolve this issue have made important gains, resulting in a large array of various climate, nature and biodiversity standards, methods and tools available today.[12] [13] Despite these efforts, no approach or standard has yet been widely adopted. Most approaches now agree that the solution is to scale results from site operations to higher levels.[14] This has been presented in several ways, but essentially it is a hierarchy aggregating environmental insights from the asset to the company to the parent company, or region insights from municipality to sovereign (Figure 1).[15]

Figure 1
Top, adapted from Stephenson, and Carbone (2021), an example indicator hierarchy, linking ground in-situ biodiversity data from a commercial site to corporate performance.

Bottom, adapted from World Bank and WWF (2020) – a hierarchy linking sub-asset assessments to corporate performance to the portfolio to national scales.[16]





Measuring environmental variables on the ground in-situ, whilst effective, is laborious, expensive and unviable at scale. ESG analysts require results ready to go at company and portfolio level, ideally assessed frequently with consistent methods to provide up to date comparable insights. As a result, alternative solutions need to be found. Satellite remote sensing is arguably a good candidate; while it will never be able to answer all questions, it is increasingly able to provide environmental insights at a global scale that are consistent, independent and repeatable at a high temporal frequency – ideal for creating consistent ESG relevant insights across the globe for millions of commercial assets. Combined with the improvements in machine learning, this leads to the realization that we are entering a world where assets, corporates and nations themselves will no longer be the key factor in disclosing their environmental impact: geospatial ESG approaches, combined with other AI developments such as natural language process (NLP), are increasingly capable of unpicking the large data trails to provide robust insight independent of the actor.

Biodiversity and many environmental variables are notoriously hard to quantify: there are no tons, degrees or centimetres of biodiversity. Species, or numbers of species, can be used as units of measurement, but each unit 'species' is not itself a consistent unit – as is, say, a ton of carbon – each species having differing impact sensitivities, rarity, range connectivity, etc. And whilst efforts are under way to develop quantifiable and comparable biodiversity metrics, such as Mean Species Abundance (MSA) or Species Threat Abatement and Recovery (STAR),[17] they have limitations (See Key Limitations – Biodiversity). Additionally, environmental risks and impacts are often non-linear, can occur over long time horizons, and materialize abruptly when they do occur, due to threshold effects or tipping points. Satellite remote sensing and geospatially derived metrics are not exempt from these challenges. Yet progress has been made over the past decades, and in the coming years, more advanced technology (See Future Developments), sensors and models will be capable of providing greater insight into near-real time trends of ecosystem health and other relevant insights.[18] Combined with improvements in machine learning, it is now inevitable that geospatial insights will improve and offer increasingly valuable data points to be integrated within traditional ESG methods.

In this paper we explore the topic of geospatial ESG, looking at the challenges and what can be achieved today both with the current open 'environmental' geospatial data portfolio and by commercial actors. This will be illustrated with three real-world case studies in Brazil, showing geospatial environmental insights, with a focus on defining impact across three different scales: project finance, corporate investment, and sovereign debt – specifically:

- Mining Projects in Brazil for Project Finance – WWF
- Soft Commodity Companies in Brazil for Corporate Investment – Global Canopy
- Environmental Performance of Brazil for Sovereign Debt – World Bank

BIODIVERSITY AND MANY ENVIRONMENTAL VARIABLES ARE NOTORIOUSLY HARD TO QUANTIFY: THERE ARE NO TONS, DEGREES OR CENTIMETRES OF BIODIVERSITY

HOW DOES GEOSPATIAL ESG ALIGN TO EXISTING ENVIRONMENTAL OR BIODIVERSITY SCREENING APPROACHES?

Traditionally, large actors like development banks have gained insights into environmental impacts through resource and time-intensive social and environmental impact assessments for specific projects – although increasingly these are integrated with remote sensing and geospatial components, modelling or a combination of methods. A ground-proofed approach, whilst excellent, is not suitable for many types of investment, where one company may have hundreds of assets and supply chains connected to tens of thousands of sites. In the absence of having ground assessments to hand, actors are forced to turn to modelled or geospatial approaches for insights.

A large range of modelling, generalist environmental and specific biodiversity footprint tools[19] have emerged to aid corporates or financial institutions (FIs) in understanding the environmental implications of various types of operations or investments. Commonly these tools combine publicly disclosed corporate information with open-source scientific datasets and then apply a custom model to define risks or impacts. Frequently they attempt to capture upstream and downstream effects, using some form of value chain analysis linked to the location of the company's production facilities and generalized biodiversity impacts or pressures. Portfolio-level outputs, commonly sum company-level assessments. All these tools are relatively new, and as such, there is very little standardisation or benchmarking to test results between tools.

Often these footprint tools, lacking direct site-level environmental impact measures, convert publicly disclosed revenue figures into production volumes as a starting point to scale impact. To achieve this, they use some means to classify the various activities of each company (e.g., GICS, NACE, FactSet's Hierarchy). These are then combined with other open-source or custom methods (e.g., EXIOBASE, ReCiPe/Life-Cycle Assessment) to translate production and resource usage into a range of environmental pressure metrics, such as land-use change, CO_2 and CH_4 emissions, and freshwater pollution. These are then converted again into biodiversity impact metrics, often via an open-source model such as the Global Biodiversity Model for Policy Support (GLOBIO).

These approaches use standard values for location, industry and activity, and as such require tailoring for each company to provide robust results. The tools frequently include geospatially derived variables within their models. Examples of these footprint focused tools include:

- Corporate Biodiversity Footprint – Iceberg Data Lab
- Biodiversity Impact Analytics – CDC Biodiversité / Carbon4 Finance
- Biodiversity Footprint for Financial Institutions – ASN Bank / Pre / CREM
- Sustainable Investment Framework Navigator – KPMG / CISL
- Portfolio Impact Analysis Tool for Banks – UNEP FI Positive Impact Initiative

On the other side of the equation, a range of geospatial 'environmental insight' focused tools have emerged. These tools tend to be designed around screening for project finance, often without pre-packaged asset data, requiring the user to upload and compile their own assessments. Examples include Global Forest Watch Pro, Ecometrica, Maphubs, and Integrated Biodiversity Assessment Tool (IBAT). Others, such as Asset Resolution, Verisk Maplecroft and Reprisk, contain asset data and can in some cases provide insight at asset, corporate and sector levels.

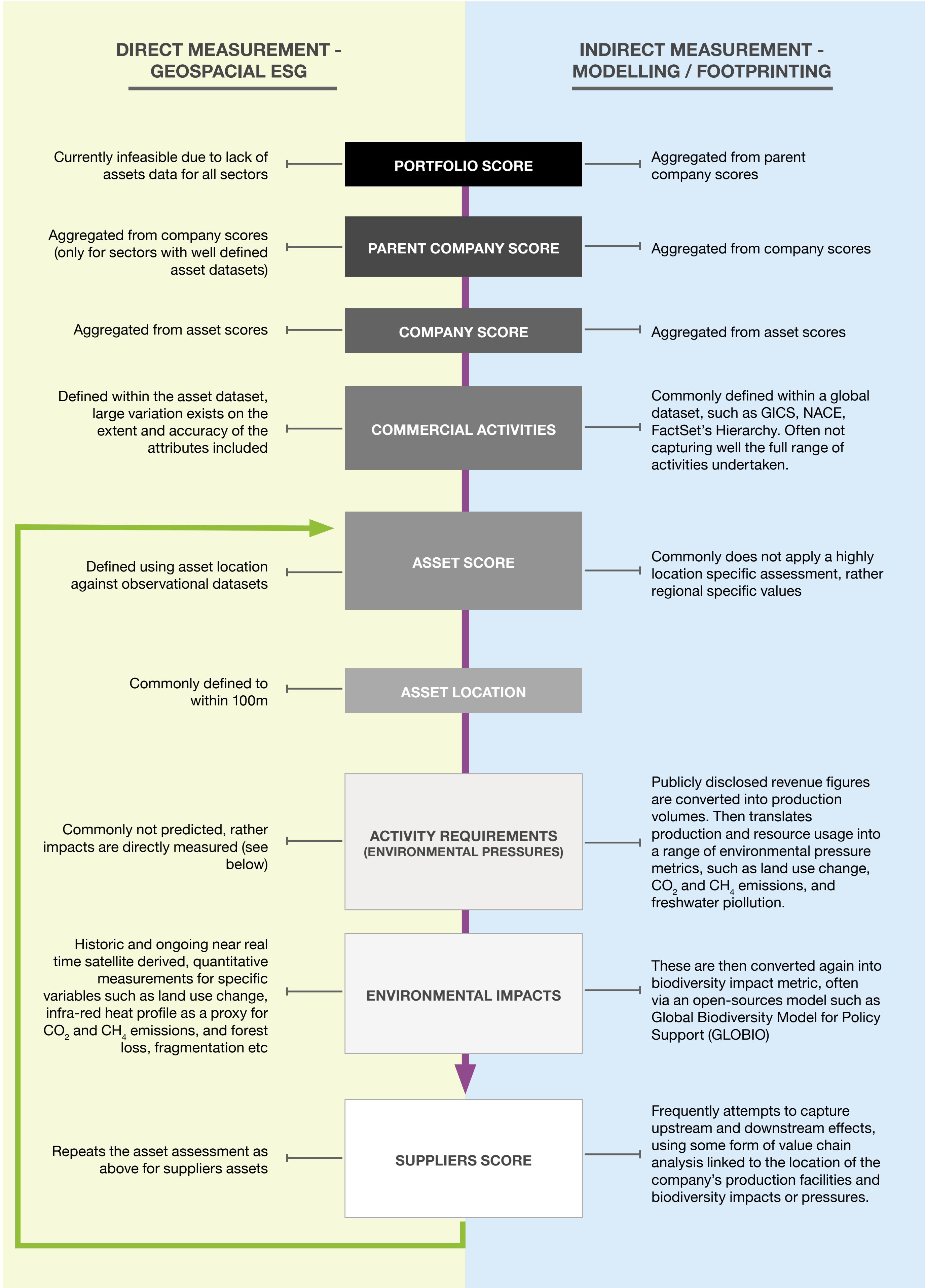
The use of geospatially derived data within modelled approaches is common. Broadly speaking, however, it is possible to categorize the two major approaches as those which focus on 1) indirect measures via modelling of financial data and sectoral classification and those which focus on 2) direct geospatially derived measurements. Neither approach is necessarily better than another; both have limitations. However, the goal is the same: to define at multiple scales as comprehensively and accurately as possible the environmental impact (and often dependencies) of a wide selection of companies.

Figure 2 simplifies the steps these two approaches often take to define environmental impact (and dependencies) at the asset scale or higher. Geospatial approaches can aid in defining the environmental impacts of commercial activity – e.g. the extent of power consumption via infra-red heat proxy, the extent of land degradation, marine oil spills, and CH_4 emissions. Importantly, compared to modelling approaches that often rely on annually disclosed data, geospatial metrics can potentially be generated at a very high granularity and temporal frequency, assuming robust asset data is continuously available. This allows potentially highly accurate independent daily, weekly and monthly metrics. Of course, improved environmentally relevant geospatial data is potentially a win for any approach as it provides more robust data which could be integrated into any method.

The next sections look at these geospatial approaches in more detail.

Figure 2 (following page)

Diagram illustrating the two approaches for corporate biodiversity environmental screening, the more established economic driven modelling approach (RIGHT), and the emergence and potential of direct measurements via geospatially driven methods (LEFT). For simplicity we have separated the two approaches; however it seems inevitable that due to data gaps in the geospatial portfolio, hybrid approaches pulling from both sides of the equation are likely to be developed.



THE FUNDAMENTALS OF A GEOSPATIAL ESG APPROACH

A geospatial ESG approach is straightforward. The location/s of an asset or a company's asset and their suppliers' assets are geolocated. Known as '**asset data**', once defined these locations or areas can be compared or modelled with '**observational data'** – datasets that provide insight. Within the environmental space, these might provide insights into variables such as a factory's heat profile as a proxy for power usage, methane emissions, or direct impacts to the natural world such as by considering overlays with protected areas, deforestation, habitat fragmentation, endangered species, habitat connectivity, biodiversity, etc.[20] **Throughout this document we assume access to robust asset data, with the necessary ownership information to allow results to be linked to specific assets, companies and then portfolios.**

More complex geospatially driven approaches are possible that consider environmental dependencies (e.g. water risks) and wider risk modelling, assessing environmental values in connection with another and not in isolation. This would consider, for example, the interrelated environmental impacts of a company's assets, all its operations globally and its ongoing impacts (and how these impacts affect other operations within the context of the immediate and global landscape); the near-real-time direct weather risks to the assets and indirect risks (e.g. extreme weather damaging supporting infrastructure); and the long-term climate implications – all relative to the asset's positive outputs (e.g. production and performance vs. its peers). **As an introductory starting point within this paper, we simplify the discussion to focus on geospatial approaches to measuring direct environmental impacts**.[21]

'ENVIRONMENTAL' OBSERVATIONAL DATA

The world of geospatial data that might be relevant as observational data is vast. Platforms like Resource Watch and UN Biodiversity Labs, with large public data portfolios, serve to illustrate the diversity and depth of some of the major environmentally relevant datasets available. The initial challenge is that a broad range of topics – from weather to soil carbon to biodiversity to an area's legal status to the net primary productivity of ecosystems and climate change[22] – might be relevant depending on the use case. As a result, thousands of datasets, either local or global, may offer value.

At a most basic level, a user can compare assets against a single observational data layer in a direct one-to-one comparison. For example, global power plants (asset data) can be compared against World Heritage Sites (observational data) to identify which power plants are within or near a World Heritage Site. Whilst useful, often parties are interested in more complex questions, such as, 'Which power plants are having the greatest environmental impact on World Heritage Sites per MWh?' To begin to answer this question[23] will require the application of many observational datasets together, in combination with other non-geospatial data points – looking at, say, the power plant's attributes: its type, fuel type, output, etc. Using these sector-specific variables, it is then necessary to consider the asset's initial environmental impact (e.g. clearance of site for construction and scaling of that impact against habitat types; endangered species presence; proximity to highly sensitive conservation sites) and ongoing impacts (e.g. CH_4 emissions, infra-red heat profiles, etc.). Where data is not available at the asset level, it might be necessary to average results regionally or apply regional datasets or some other measurement (see Case Study Two). This approach requires a wide-ranging and up-to-date set of environmentally relevant observational datasets for the analyst to draw upon.

With the geospatial ESG approach for environmental impact developing, there remains confusion around which observational datasets should be applied. Which are the most essential? And what exactly can this data tell us separately and in combination? What data is missing and how might it be improved in the future? How should methods be tailored to specific sector needs? To begin to answer these questions, it is first necessary to understand the data realities and the issues currently shaping geospatially driven methodologies.

In the next section (Key Limitations) we consider the constraints of the current data situation by looking at a portfolio of open 'environmental' geospatial data. Here, as an example drawing upon the geospatial data portfolio of the UN Biodiversity Lab, a UN website that is focused on curating and managing a robust environmental geospatial open library to support nations' delivery of the SDG and CBD goals. As such it serves as a robust example of the current authoritative and relevant data available and useful for considering environmental variables using globally consistent datasets. It by no means captures all the data available but provides a good indicative sample of the open global scale datasets available.[24]

KEY LIMITATIONS FACED WHEN APPLYING THE OPEN 'ENVIRONMENTAL' OBSERVATIONAL DATASETS FOR GEOSPATIAL ESG APPLICATION

Geospatial datasets, either alone or in combination with other datasets, can be used to provide ESG insights on 'environmental' variables and even biodiversity impacts and risks. It is not yet clear what the data requirements are for geospatial ESG, where standards are still to arise. Different applications will have differing data needs – for example, sovereign debt insights will differ from project finance. However, several assumptions can be made. Firstly and most importantly, the data must be capable of meaningfully capturing the environmentally relevant variable. Secondly, they must provide insights at a meaningful resolution: results at 40 km may suit landscape, state or national insights but may lack the granularity to report on the impacts of specific commercial assets. Thirdly, they must provide insights at a high enough frequency to be meaningful to the analyst but also manage to capture events – for example sampling once a year is not suitable for capturing CH_4 emissions. Finally, datasets need to be consistent, to enable trends to be calculated, where for most sovereign applications five years of data seems to be required.

Considering these variables against the current open data portfolio raises some interesting issues which potentially act as a limitation on insights. Here we review six key issues commonly found within the open data portfolio:

- **Temporal consistency**
- **Spatial resolution**
- **Accuracy**
- **Data interdependencies**
- **Relevancy**
- **Challenges of 'Biodiversity'**

Figure 3 (following page)

A visual illustration of temporal coverage of 105 open and commonly used environmentally relevant geospatial datasets.

1. TEMPORAL CONSISTENCY

Issue: **Open[25] environmentally relevant datasets have poor temporal consistency**.

To illustrate this point, below we reviewed 105 data layers[26] listed on the UN Biodiversity Lab, highlighting in blue every year a data layer has a measurement. Only 40 data layers (38%) had values for more than one year. Only 20 (19%) had consistent records for over five years.

The lack of data points over time is compounded within some datasets, such as the Global Human Modification Index, where, due to different methodologies applied, different years are not directly comparable. Finally, research and development and then publication delay have an impact, where frequently several years may have passed between developing products and publishing results. For example, the Biodiversity Intactness Index was published in 2016, reporting results for 2005.

Cause – Global datasets are expensive to develop and maintain. Frequently, data layers are developed for academic publication. Once the publication is achieved there may not be resources or incentive to regularly update and produce year on year updates. Or technology or methods may improve, outdating the approach and data product. Those data layers which are produced consistently at high frequency are almost always those backed by major programmes, such as Global Forest Watch, or major databases such as the World Database on Protected Areas.

Implications – Geospatial ESG insights are only of value if they are correct. In general terms, the older the observational dataset applied, the greater the potential that the data will be out of date and incorrect as a current measurement. The lack of consistency over time also limits the ability to consider trends over time, where ideally at least five years of consistent data is required. Low temporal frequency, with only a few datasets offering monthly updates, also makes it impossible to monitor emerging issues in near-real-time or track trends at a finer scale, or in some cases define the initial impact of projects.

2. ACCURACY

Issue: The accuracy of environmentally relevant spatial datasets is not absolute.

To help understand how this data can be applied, it is necessary to understand a little about the data. Firstly, there are two major types: **vector,** and **raster** data:

- Shapes (vector files) often define man-made delineations, country boundaries, protected areas, indigenous areas, key biodiversity areas, marine protected areas, important marine mammal areas, estimated species ranges, etc.
- Grids of pixels (raster files), often used to represent continuous phenomena or variables, are equal-area squares with a given specific value, frequently used to provide global maps of land cover, elevation, forest loss, forest gain, flood risk, ground carbon, extreme weather risk, human disturbance, biodiversity indices, species counts, habitat connectivity, etc.

Raster Datasets

Cause – Raster layers with environmental relevance are often based on complex image classification algorithms of satellite imagery, in which methodological choices have had to be made to define how to interpret images. Ground validation, required to improve the accuracy of data products, is often costly and as a result limited. In addition to the methodological challenges, some classifications provided might not be narrow enough for the sought application – e.g. 'forest', and not 'pine forest'. Modelled layers are frequently developed from data sources which contain data gaps, gaps that are often not expressed in the results, potentially providing a false impression of their accuracy.[27]

Implications – Fortunately, most major open datasets are the results of peer-reviewed research, and a high standard exists. As such an assumption of a fair degree of accuracy is often possible. This is combined with the consideration that a fair degree of imprecision is likely to be tolerated in geospatial ESG, where the goal is often high-level screening to find outliers rather than to delineate between specific values – although as attention on the subject increases, and as data products are increasingly used as decision variables within the financial sector, we can expect to see greater scrutiny placed on the accuracy of products used. However, caution should always be applied, and accuracy should not be assumed.

Vector Datasets

Cause – Within vector datasets – shapes defining areas such as protected areas – accuracy is not absolute, and the boundaries of given areas are not always correct. Often situations arise where there is no 'agreed' boundary, with different stakeholders presenting different delineations. This is a common issue with border disputes between countries. Beyond basic errors, large environmentally relevant vector datasets often contain technical faults, such as topology or geometry errors, making the datasets difficult and in some cases impossible to analyse without a significant correction.

Implications – Error or disagreement on boundaries for an area (e.g. a protected area, country, indigenous area) as defined within vector datasets means that results reported may not be accurate or may be perceived as inaccurate by some stakeholders. Technical errors slow assessments and waste resources and reduce the application of the dataset.

Any systematic or random error is undesirable in terms of generating useful insights and undermines the potential strength of geospatial insights, although most boundary errors can be addressed by reporting results conservatively with buffer areas included or with error margins. Perceived error is more challenging to address and has slightly unusual ramifications, for example, government officials may not readily accept results generated for sovereign debt geospatial assessments of their nation if they disagree with the boundaries applied in the assessment. Added to this issue, an asset's area may change over time. This issue, or its potential, needs to be addressed when designing metrics. For example, at a simple level, total forest loss within a palm oil producer farm is not directly comparable over time if the producer's farm changes in area, but total forest loss, per km^2, would be comparable.

3. SPATIAL RESOLUTION

Issue: Open environmentally relevant raster datasets often have a low spatial resolution.

The value of an observational dataset rests in part on how frequently it is updated, but also on its spatial resolution. This refers to how large the pixel size is (Figure 4). Those with a fine resolution (under 30m) allow more detailed insights; above 30m, necessary detail, such as deforestation or land degradation, begins to be averaged. Although as we will see this is not relevant for all applications – the resolution required depends on the task in question. Within the data portfolio, assessed resolution ranged from approximately 30m at the equator to 100km. Of the 105 layers assessed, 24 (22%) had a resolution of or below 100m.

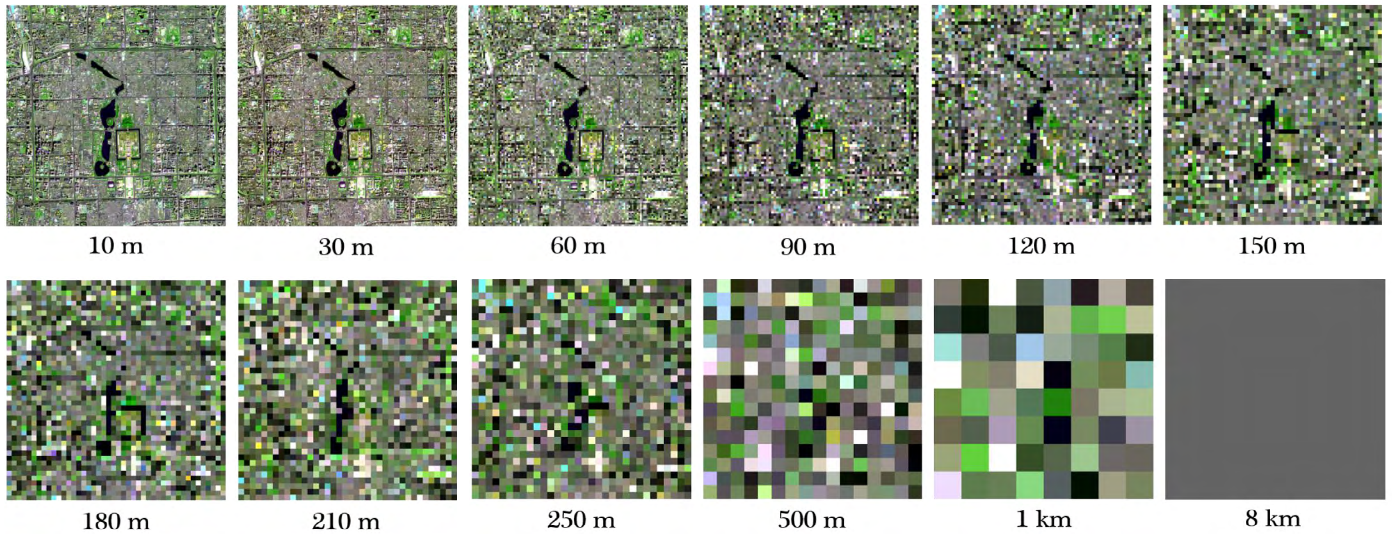


Figure 4
A graphical representation of spatial resolution, illustrating how rapidly detail is aggregated at relatively high levels of resolution. Taken from Tian et al., 2020 images show in false colour (Red, NIR, blue bands as R-G-B images of a subregion in Beijing at different spatial resolutions.[28]

Cause – Almost all openly available global remote sensed derived data products have been developed based on freely available ESA and NASA satellite imagery. This imagery resolution has commonly been a limit on the resolution of global environmentally relevant datasets. Whilst high-resolution imagery is commercially available up to 30cm, the cost of acquiring the imagery and then the computational power required to convert these images into useful insights means this is unviable for almost all academic and NGO applications, where even developing 30m resolution layers with freely available imagery requires significant computing resources. As a result, many of the finer resolution data products rely on donated resources from the tech sector, such as Google, Microsoft, or others. Modelled layers which use ground data face a similar compute restriction, often limiting resolution to around 1km.

Implications – Often commercial assets are relatively small (e.g., individual power plants, roads, mines, farms, etc.). Frequently users are interested in topics such as deforestation, land-use change or pollution events, at a fine scale to link to specific assets, which typically requires high-resolution observational datasets. However, there are many exceptions where high-resolution data is not required, such as some national scale indicators. It could be argued that many of the critical environmental data products relevant to geospatial ESG insights are limited by spatial resolution. However, this is unlikely to be the case for long since, as satellite technology develops, we can expect to see more and more high-resolution imagery and derived data products become obtainable at a viable price point.

4. DATA INTERDEPENDENCIES

Issue: Environmentally relevant observational datasets may draw from the same source data.

Cause – Due to the challenges and efforts in developing global geospatial data products, researchers often use one or multiple existing spatial datasets to build a new product, for example, 'Terrestrial Ecoregion Protection – 2018'[29] is a combination of:

- IUCN and UNEP-WCMC (2018). The World Database on Protected Areas (WDPA), April 2018. Cambridge, UK: UNEP-WCMC. Available at: www.protectedplanet.net
- Olsen, D.M. et al. (2001). Terrestrial ecoregions of the world: a new map of life on Earth. BioScience, 51(11): 933-938.
- The Nature Conservancy (2012). Marine Ecoregions and Pelagic Provinces of the World. GIS layers developed by The Nature Conservancy with multiple partners, itself combined from
  - Spalding et al. (2007) Marine ecoregions of the world: A bio-regionalization of coastal and shelf areas. Bioscience 57: 573-583.and Spalding et al. (2012) Pelagic provinces ecoregions of the world: A biogeographic classification of the world's surface pelagic waters.
  - Ocean & Coastal Management 60: 19-30. GIS DATA (the non-cut on the coastline version has been used) downloaded on 20160720 from http://data.unep-wcmc.org/datasets/38.

Implications – This means that errors or issues in prior datasets can be compounded. In addition, the 'new' product may be formed of much older datasets and may not be as up-to-date as first considered. Finally, as actors move towards more complex geospatial assessments and merge multiple datasets in combination, there is the potential for duplication of values within the model, with the same dataset effectively influencing results multiple times.

5. RELEVANCY

Issue: The current open environmentally relevant datasets lack topic coverage.

A robust overview of environmental impacts (and other potential use cases) for ESG application requires observational datasets which provide relevant insights into many different subject areas, such as above-ground biomass, net primary productivity, vegetation height, fragmentation, soil moisture and species abundance, at high spatial and temporal frequencies.

Whilst a wide portfolio of geospatial data is available, it does not always explicitly capture the specific metrics required. Confusing the situation is the fact that there are often tens of geospatial datasets available for a single topic, all with slightly differing methodologies. The analyst faces the challenge of identifying which one to apply. This is worsened by the poor temporal consistency (as outlined above), where datasets are often not updated, forcing actors to switch between datasets, undermining the consistency of results and their ability to track metrics over time.

Cause – Beyond the practical costs and challenges in updating global data products, there is also the technical difficulty in quantifying variables for some topics, where some remote sensing measurements are simply easier to achieve than others. As such, there is often a bias towards the more technically feasible topics.

Implications – As demand increases from financial investors to be able to better define their 'biodiversity' impact or risk exposure and various 'E' metrics, there is an emerging risk that until the various stakeholders work to overcome complex technical challenges, the current data gaps will be filled with subpar data products. Fortunately, there have long been calls for an improved environmental data portfolio for wider conservation goals,[30] and there are established efforts underway working to resolve this issue.[31] Other technical developments are also occurring, which are likely to combine and complement the remote sensing efforts, see Future Developments.

6. BIODIVERSITY

Issue: 'Biodiversity'[32] is extremely difficult to capture and define in near-real-time[33] at a global scale.

It is often claimed by data providers that their geospatial data, model or tool is robust and provides holistic insight into biodiversity impacts or related areas. However, we would argue that at this time, no team, group or product has yet achieved a means of defining the impact of commercial operations on biodiversity, at a global scale at a high temporal frequency.

If, for example, we consider the Integrated Biodiversity Assessment Tool (IBAT), which is often presented as a method of screening for biodiversity risk, we can explore some of the challenges. IBAT is a highly useful data offering primarily made up of three global datasets: Protected Areas (WDPA), Key Biodiversity Areas (KBAs) and the IUCN Red List of Species. Protected Areas (PA) and KBAs may or may not have a high level of biodiversity within them; some may be highly degraded, some may be pristine. From the source dataset itself, the differentiation of intactness of sites is not possible. Since there is no near-real-time input on the physical status of the intactness of assets, results in some cases may not be well-grounded. For example, although the WDPA is updated monthly, if a PA has recently been converted to, say, a palm oil plantation, this would not necessarily be reflected rapidly within the IBAT data, requiring further triangulation with external datasets outside of IBAT by the user and likely additional licensing rights. These datasets and the others available of course provide valuable insights, but even the most robust data offerings have challenges. This means that in almost all cases, for geospatial ESG application caution and additional analysis is required when applying them.

Cause – In the race to compete and provide products for the growing demand, actors may inadvertently overstate the relevancy or accuracy of their products. Or conversely, various FIs keen to rapidly upskill in this space may not have the time or resources, or the incentive, to scrutinize the solutions they are offered.

Implications – Assuming that a dataset meaningfully captures an environmental metric more than it actually does creates the potential for actors to falsely believe their exposure is less than it is, or that specific companies or assets have higher exposure. This ultimately has the potential to aid greenwashing, derailing trust in the ESG process of trying to realign capital to support nature recovery, or to slow the effectiveness of the realignment.

REFLECTIONS ON THE CURRENT OPEN 'ENVIRONMENTAL' DATA LANDSCAPE

The open[34] data portfolio assessed in this document is by no means comprehensive. It does, however, highlight the general themes and the common issues currently faced by those providing environmental geospatial ESG solutions drawing upon these reserves. Actors within the commercial space, as we will explore, have developed workarounds to some of these challenges. Yet often the underlying data used by commercial operators comes from publicly available data sources provided by NGOs, IGOs, academia or multilaterals. Indeed, due to the irreplaceability of these global environmental datasets, where only one or two exist, future commercial geospatial ESG developments will most likely in many cases be restricted by these datasets unless radical solutions are found.

From a geospatial ESG perspective, perhaps the most pressing issue is the that surrounding the temporal and spatial resolution of datasets. The graph below (Figure 5) illustrates this: out of the 70 raster datasets assessed, most (46) have a low spatial resolution and a poor temporal resolution; only a few (6) can be considered to have both high spatial and temporal resolution.

If geospatial ESG is to deliver meaningful results, it will require a more temporally consistent and wider environmental data portfolio to work from, particularly around 'biodiversity'. Perhaps the most established push for a unified plan for monitoring global biodiversity comes from the Group on Earth Observations Biodiversity Observation Network (GEO-BON), via its common framework of essential biodiversity variables (EBVs). A recent paper by Skidmore *et al* (2021) proposed a set of 30 key remote sensing biodiversity products[35] for global biodiversity monitoring to fill data gaps for wider conservation purposes, such as tracking performance to global targets, United Nations Sustainable Development Goals (SDGs) and Aichi targets. The paper,[36] and others before it, have repeatedly highlighted the need for harmonized, open, accurate, repeatable and reproducible, analysis-ready remote sensing biodiversity products (and with that the need for more ground-truthed biodiversity data) for national monitoring,[37] policymakers and scientists – a need we echo here, but for a newer use case: the geospatial ESG application for the financial sector.

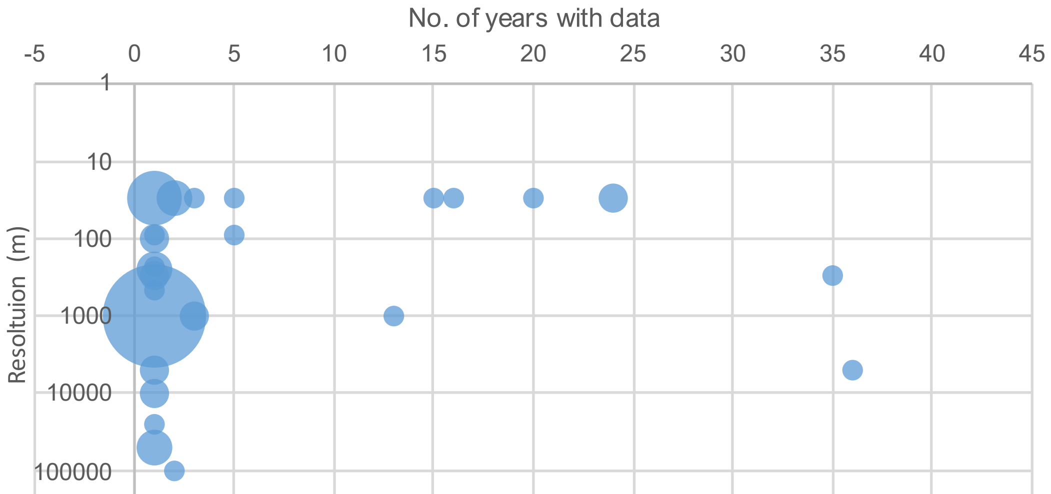


Figure 5

Graph showing the spatial and temporal resolution of 70 raster layers assessed from the UN Biodiversity Lab data portfolio. Circle size indicates number of datasets.

LINKING IN-SITU OBSERVATIONS WITH REMOTE SENSING EFFORTS WILL BE ESSENTIAL TO CREATING IMPROVED DATA PRODUCTS.

Within the commercial space, actors such as Ecometrica[38], Earth Knowledge[39] and others have built upon the open data space to create improved data portfolios, generating their own data products to fill temporal gaps or improved resolution through techniques like backfilling. However, many of the key environmental topics, such as biodiversity, cannot be developed purely from remote sensing but require in-situ ground data much of which is held by the NGOs or intergovernmental institutions. Linking in-situ observations with remote sensing efforts will be essential to creating improved data products. And until this is resolved, open or private sector developments are likely to continue to face restrictions or will require entirely novel technical approaches to improve the global environmental data portfolio.

The question that comes next is, considering these limitations, what can be achieved now? To give insight into the extent of what is possible, we provide an example from the commercial space on the next page, showing how complex models are capable of overcoming many of the data limitations to provide greater insights than the sum of their geospatial parts. From there we explore three case studies across multiple scales in Brazil, showcasing step by step the various insights which can be gained and the various data challenges involved, starting at the asset level, looking at mining in Brazil.

BOX ONE

EARTH KNOWLEDGE

Authors: Frank A. D'Agnese, President and CTO, Earth Knowledge, Inc. and Julia Armstrong D'Agnese, CEO, Earth Knowledge, Inc.

The Earth Knowledge Planetary Intelligence Platform continually assesses Earth systems. Our platform leverages a 'digital twin' of the Earth integrating authoritative data and models of the Earth's interconnected systems, from the subsurface to the upper atmosphere. This digital Earth represents the varying conditions of landscapes and seascapes at multiple spatial and temporal resolutions, from approximately 125 years into the past to 150 years into the future.

The Earth Knowledge Platform translates scientific data, geospatial data and Earth-systems models into 300+ indicators related to the direct drivers of global change and the commonly described three pillars of sustainability (Natural Capital, Social Capital, and Economic Capital). These direct drivers of global change, which lead to biodiversity loss and habitat degradation, include climate change, pollution, invasive species and disease, over-exploitation of natural resources, and land and sea conversion. The indicators help assess global change and sustainability actions and provide a quantitative way to measure impacts and related potential risks and opportunities at any location on the globe.

Earth Knowledge's framework aligns to the same five drivers of global change developed by the IPBES in their global assessment of biodiversity and ecosystem services,[40 41] the WWF in their Living Planet Database and Report,[42] the WEF in their Nature Risk Rising Report,[43] and which were originally defined by the IUCN in their Standard Lexicon of Biodiversity Conservation.[44] This fundamental alignment of the Earth Knowledge's Indicators Framework, or indeed any platform, to these authoritative bodies is foundational. It provides consistency in process and language so that more direct translation can be made between science conclusions and global change and sustainability outcomes evaluated by financial institutions.

Vitally the data generated from Earth Knowledge Indicators are structured to identify and forecast both discrete environmental processes and the interrelated resulting conditions of global change on biodiversity and other aspects of natural capital. Each Indicator is a composite measure of different conditions aggregated at multiple spatial resolutions at different time periods for specific locations across a landscape or a seascape.

THE SPECIFICS

Earth Knowledge generates its 'digital twins' by constructing and running numerous Earth system and Earth subsystem process models to characterize past, present and potential alternative future environmental processes and conditions. Where required, lower resolution (more global) data or model outputs are appropriately downscaled using spatial, statistical or dynamical downscaling methods that are suitable for the data and the model from which the data originated.

Process models used to describe biophysical processes at multiple spatial and temporal scales must meet several key criteria in order to be used. These include that the biophysical process models must:

1. Be developed or available in the public domain
2. Have undergone significant peer review in many different journals and/or organizations
3. Be used in many different landscape environments and settings
4. Be used in many different geographic locations
5. Be applicable at multiple spatial and temporal scales and
6. Be used by a broad user community

For each Earth system and Earth subsystem model, Earth Knowledge identifies and selects authoritative data sources based on:

1. Global uniformity and extent (global, regional, locally specific data set)
2. Date of collection (or future projection)
3. Spatial resolution
4. Methodology of data acquisition and development
5. Official verification of the data developers and their organization and
6. Assessment of their source organization's quality assurance and quality control procedures

Candidate source datasets are profiled, qualified and sampled to establish their suitability for acquisition and processing.

Once the models are calibrated and evaluated to determine how well the models represent natural conditions over the 125-year historical period, the models are then re-run under varying conditions that represent different potential future states that may occur as a result of climate change and other forms of global change.

Future projections of a 150-year period are calculated beginning in 1950 and simulated through to 2100. The overlap period from 1950 through 2020 is used so that there is sufficient repetition in the historical model and the forward-looking projections to determine the potential for any model bias that could exist that may be introduced from field observation data.

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CASE STUDY ONE

ASSET LEVEL ASSESSMENT – MINES IN BRAZIL – WWF

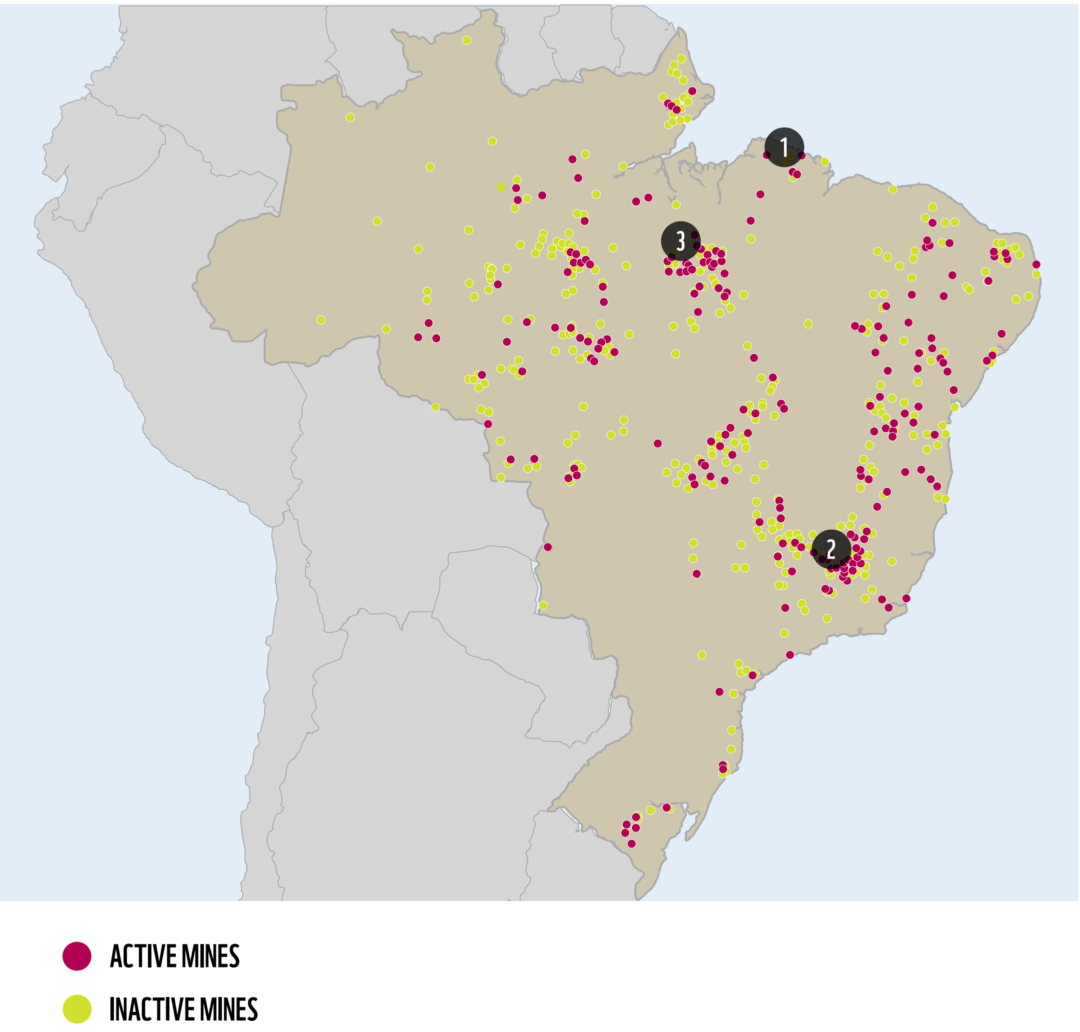
To illustrate the value of a geospatial approach at the asset level, WWF's Conservation Intelligence team[45] directly compared all commercial mines (763) within Brazil against several environmentally relevant vector and raster observational datasets. Three case mines are used throughout to illustrate the various complications which arise even in the most basic assessments. The example mines are as follows: 1) Aurizona (gold) operated by Equinox Gold Corp; 2) Capanema (iron ore) operated by Vale S.A.; 3) Northern System (iron ore) operated by Vale S.A (Figure 6).[46]

The results can be presented in a variety of ways depending on the user's application. Directly, each asset versus each observational dataset, or each asset impact modelled in some way against multiple observational datasets in combination. Or, asset scores can be aggregated to each parent company to provide insights at a parent level rather than at an individual asset level (explored in the next case study). To aid understanding of the approach, we focus here on directly reporting results per variable at the asset level. Results can of course be integrated alongside other traditional ESG metrics.

Figure 6

All mines within Brazil and the locations of the three mines used to illustrate basic issues in geospatial ESG assessments:

1) Aurizona (gold) operated by Equinox Gold Corp
2) Capanema (iron ore) operated by Vale S.A.
3) Northern System (iron ore) operated by Vale S.A.



BOX TWO

SATELLITE IMAGERY – VISUAL ASSESSMENT

During a technical geospatial assessment, it's worth noting the value of access to time-lapse satellite imagery and satellite imagery on demand. This provides an ESG analyst a rapid means of placing the project in a spatial and temporal context, without needing to source any additional details. Where is it? What surrounds it? When did the project start (if post 1980s)? What was the status of the environment before the project was initiated? How has the project expanded? Time-lapsed imagery can rapidly help provide an analyst with context to these questions, by effectively playing a short ten second video of how the site has changed since the mid-1980s. For example, below is freely available NASA and ESA imagery showing one of the three mining sites, Aurizona, from the 1980s to 2020/21. It shows that the site was mangrove forest in 1986, developed in 2013, and expanded up to the present, with the tailing dam increasing in size.

Of course, if you have the necessary resources, this data can be quantified, as outlined on Page 36.

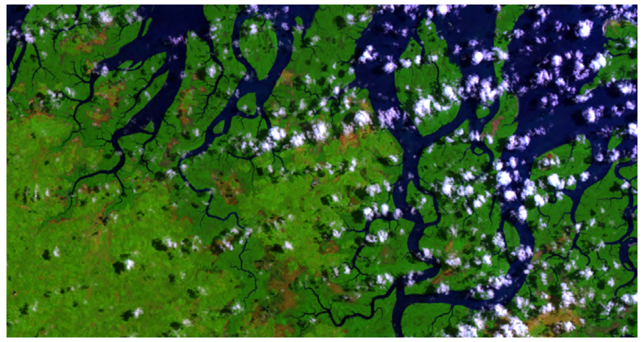


Figure 7
Aurizona site limited mining activity –
Landsat – 27th August 1986

Figure 8
Aurizona site limited mining activity –
Landsat – 8th October 2013

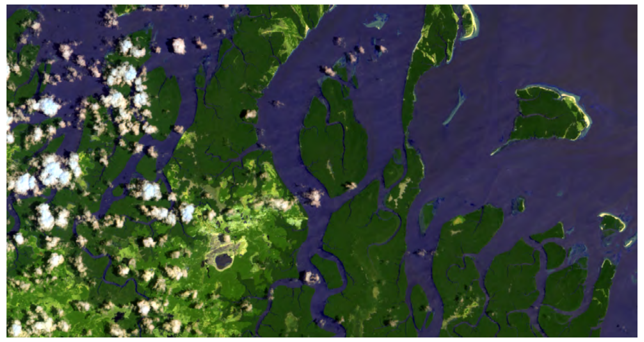


Figure 9
Aurizona site mining activity –
Sentenel 2 - 4th October 2020
(Rendered Shortwave Infared)

Figure 10
Aurizona site mining activity –
Sentenel 2 - 4th October 2020

METHOD

Mining projects as defined by S&P Global Metals and Mining dataset (data sourced as at March 2021) were given a 1km² area[47] and compared using ArcGIS 10.8.1 against several vector layers:

- Protected Areas, World Database of Protected Areas, 2021[48]
- Key Biodiversity Areas (KBAs), 2021
- World Heritage Sites, 2021

We also considered Brazil's mines against several openly available raster layers:

- Ecoregions[49]
- Biodiversity Intactness Index[50]
- Ground Carbon[51]
- Forest Loss, 2019[52]
- Forest Structural Condition Index (FSCI), 2020 – data for the Tropical and Subtropical Moist Broadleaf Forests Biome[53]
- Forest Structural Integrity Index (FSII), 2020 – data for the Tropical and Subtropical Moist Broadleaf Forests Biome[54]

Subdividing mining assets into categories, such as the ecoregion, elevation, etc., allows us to use that data point to later adjust other variables against. For example, the same mine in open grassland would have differing immediate and ongoing impacts if in a different habitat, say rainforest. Here, as one example, we use 'Ecoregions' to illustrate the approach, but more complex approaches can use any number of these differentiating variables.

Other observational layers are used to provide direct measures. Any number of observational datasets could be applied, using both static and dynamic inputs (e.g. near-real-time fire data or live feed weather data). Here we consider just a small number to describe the concept. In more detailed assessments it is common to consider 50+ observational datasets with interdependencies. Each dataset, depending on its design, needs to be treated differently to achieve useful insights. Some can be considered as is, without processing; for example, the Biodiversity Intactness Index provides a simple value that can be extracted and averaged. Most, however, require analysis, such as forest fragmentation, which needs to consider the length of fragmented habitat linked to the linear infrastructure of the mine site to provide insight into the mine's associated secondary impacts.

RESULTS

In total, 763 commercial mines were identified within Brazil, of which 263 (34%) are considered 'active'. Overall, out of the 263 active mines, 31 overlapped with KBAs, 26 of which were entirely within KBAs. For Protected Areas, 40 active mines overlapped with one or more protected areas,[55] 22 of which were entirely within PAs. Only one currently inactive mine was identified within a World Heritage Site within Brazil.

Each mine site was scored against the example geospatial layers: defining ecoregions, the mean score for Biodiversity Intactness Index, Ground Carbon, Forest Structural Condition Index, Forest Structural Integrity Index, and total area of Forest Loss within a simple 1km^2 circle[56] around each mine site. The three example mines had the following results;

Mine Name	Aurizona	Capanema	Northern System
Ecoregion	Mangroves	Tropical & Subtropical Grasslands, Savannas & Shrublands	Tropical & Subtropical Moist Broadleaf Forests
Biodiversity Intactness Index (Mean Score)	0.94	0.66	0.73
Ground Carbon (Mean Score)	9650	8700	0
Forest Loss 2019 (km^2)	0.99	0.0026	0.0215
Forest Structural Condition Index (FSCI) (Mean Score)	No Data	No Data	1.26
Forest Structural Integrity Index (FSII) (Mean Score)	No Data	No Data	0.12
Protected Areas (Area Overlap – km^2)	6.28[57]	3.13	3.14
Key Biodiversity Areas (Area Overlap km^2)	3.14	3.14	3.14

Figure 11 – Table showing the results for the three case study mines.

Once the above data are pulled together, it is possible to begin to build simple high-level 'environmental' geospatial screening for commercial mines, using relative rankings to show outliers for each observational dataset. However, there are some additional considerations. For example, many of the observational datasets above are 'forest' related (i.e. forest loss, ground carbon, FSCI, FSII). Consequently, we risk biasing scores towards mines in areas with high forest cover vs. mines in areas without forest cover, e.g. savanna. Here benchmarked weightings on the ecoregion type could address these implications, or alternatively, users may be interested to identify mines with high risk to topical forest. Of course, any real application would need to carefully consider the application of observational datasets to best meet the needs of its intended application.

The results for 50 mines are shown in Figure 12, illustrating how this method offers a high-level means to rapidly and consistently screen the active mines identified in Brazil, or indeed all mines globally. Out of the three case study mines, all three are highly ranked, with Aurizona highest. This provides a useful high-level overview, but as outlined in the next section, it is vital to dig into the data further to understand the results.

Figure 12 (Following page)

Table showing a selection of the scores generated for the observational layers run against all active mines in Brazil, reporting 50 example mines.[58]

Property Name	List of Owners	Ecoregion Name	Score	Biodiversity Intactness Index Score	Ground Carbon Score	Forest Loss - 2019 Score	FSCI Score	FSII Score	Protected Areas Score	Key Biodiversity Areas Score
Pitinga	Industrias Nucleares Do Brasil SA (Owner) 100%	Tropical & Subtropical Moist Broadleaf Forests	6.66	0.15	0.35	0	0.56	0.79	2.04	1.28
Salobo	Vale S.A. (Owner) 100%	Tropical & Subtropical Moist Broadleaf Forests	6.6	0.14	0.35	1.54	0.09	0.02	0.68	1.28
Boa Vista	GoldMining Inc. (Optionor) 84.05%; Boa Vista Gold Inc. (Optionor) 15.95%	Tropical & Subtropical Moist Broadleaf Forests	6.6	0.15	0.35	0.35	0.53	0.74	0.68	1.28
Salobo West	Vale S.A. (Owner) 100%	Tropical & Subtropical Moist Broadleaf Forests	6.59	0.15	0.35	0	0.58	0.82	0.68	1.28
Morro Dos Seis Lagos	Cia Brasileira de Metalurgia e Mineracao (Owner); CPRM (Owner)	Tropical & Subtropical Moist Broadleaf Forests	6.59	0.14	0.35	0	0	0	2.04	1.28
Serra Norte	Vale S.A. (Owner) 100%	Tropical & Subtropical Moist Broadleaf Forests	6.58	0.12	0.35	0.96	0.18	0.05	0.68	1.28
Xingu	Unnamed Owner (Owner) 100%	Tropical & Subtropical Moist Broadleaf Forests	6.57	0.15	0.35	0.41	0.51	0.72	0	1.28
EMA	BBX Minerals Limited (Optionee) 100%; Private Interest (Optionor)	Tropical & Subtropical Moist Broadleaf Forests	6.57	0.15	0.35	0.03	0.64	0.9	0	1.28
Alemao	Vale S.A. (Venturer) 67%; Federal Government of Brazil (Venturer) 33%	Tropical & Subtropical Moist Broadleaf Forests	6.56	0.13	0.35	0.03	0.39	0.39	0.68	1.28
Rio Cristalino	Colossus Minerals Inc. (Owner) 100%	Tropical & Subtropical Moist Broadleaf Forests	6.56	0.14	0.35	0	0.59	0.83	0	1.28
Amazonas	Potassio Ocidental Mineracao Ltda. (Owner) 100%	Tropical & Subtropical Moist Broadleaf Forests	6.56	0.15	0.35	0	0.56	0.79	0	1.28
Estanho de Rondonia SA	Companhia Siderúrgica Nacional (Owner) 100%	Tropical & Subtropical Moist Broadleaf Forests	6.55	0.12	0.35	0.21	0.16	0.23	0.68	1.28
Aurizona	Equinox Gold Corp. (Owner) 100%	Mangroves	6.55	0.14	0.17	0.5	0	0	1.36	1.28
Bahia	Tecstones Geologia Ltda (Owner) 55%; Private Interest (Owner) 45%	Tropical & Subtropical Moist Broadleaf Forests	6.55	0.12	0.35	0.08	0.37	0.11	0.68	1.28
Trauira	BTG Pactual Mining S.A. (Owner) 88.08%	Mangroves	6.55	0.16	0.11	0.24	0	0	1.78	1.28
Para-Amazonas	Cowley Mining plc (Owner) 100%	Tropical & Subtropical Moist Broadleaf Forests	6.54	0.15	0.35	0.22	0.36	0.51	0	1.28
N5	Vale S.A. (Owner) 100%	Tropical & Subtropical Moist Broadleaf Forests	6.54	0.12	0.35	0.36	0.08	0.02	0.68	1.28
Azul	Vale S.A. (Owner) 100%	Tropical & Subtropical Moist Broadleaf Forests	6.53	0.12	0.35	0.26	0.05	0.01	0.68	1.28
Salobo South	Unnamed Owner (Owner) 100%	Tropical & Subtropical Moist Broadleaf Forests	6.53	0.15	0	0	0.61	0.86	0.68	1.28
Vale do Ribeira	Cia De Pesquisa De Recursos Minerais (Owner) 100%	Tropical & Subtropical Moist Broadleaf Forests	6.53	0.14	0.09	0.02	0.54	0.57	0.68	1.28
Serra Sul	Vale S.A. (Owner) 100%	Tropical & Subtropical Moist Broadleaf Forests	6.52	0.13	0.35	0.07	0	0	0.68	1.28
Iporanga	CPRM (Owner) 100%	Tropical & Subtropical Moist Broadleaf Forests	6.52	0.13	0.35	0.01	0.5	0.14	0	1.28
Brazil	Unnamed Owner (Owner) 100%	Tropical & Subtropical Grasslands, Savannas & Shrublands	6.52	0.14	0.16	0	0	0	1.36	1.28
Patrocinio	Belo Sun Mining Corporation (Owner) 100%	Tropical & Subtropical Moist Broadleaf Forests	6.51	0.14	0.17	0.55	0	0	0.68	1.28
Corrego do Sitio	AngloGold Ashanti Limited (Owner) 100%	Tropical & Subtropical Moist Broadleaf Forests	6.51	0.14	0.16	0.25	0.3	0.06	0.63	1.28
Igarape Bahia	Vale S.A. (Venturer) 87%; Federal Government of Brazil (Venturer) 13%	Tropical & Subtropical Moist Broadleaf Forests	6.51	0.12	0.18	0.02	0.23	0.31	0.68	1.28
Volta Grande	Belo Sun Mining Corporation (Owner) 100%	Tropical & Subtropical Moist Broadleaf Forests	6.5	0.13	0.35	0.29	0	0	0	1.28
Santa Barbara	Companhia Siderúrgica Nacional (Owner) 100%	Tropical & Subtropical Moist Broadleaf Forests	6.49	0.13	0	0	0.37	0.52	0.68	1.28
Ribeirao do Carmo	Cia Minas da Passagem (Owner) 100%	Tropical & Subtropical Moist Broadleaf Forests	6.49	0.13	0.16	0.23	0.39	0.23	0	1.28
Paragominas	Norsk Hydro ASA (Owner) 100%	Tropical & Subtropical Moist Broadleaf Forests	6.48	0.12	0.17	0.49	0.09	0.05	0	1.28
Capanema	Vale S.A. (Owner) 100%	Tropical & Subtropical Grasslands, Savannas & Shrublands	6.48	0.1	0.16	0	0	0	0.68	1.28
Cata Preta	Ouro Preta Mineracao Limitada (Owner) 100%	Tropical & Subtropical Grasslands, Savannas & Shrublands	6.47	0.13	0.16	0.43	0	0	0	1.28
Cata Preta	Ouro Preta Mineracao Limitada (Owner) 100%	Tropical & Subtropical Moist Broadleaf Forests	6.47	0.13	0.16	0.43	0	0	0	1.28
Vetria	Rumo S.A. (Venturer) 50.38%; Vetorial Siderurgica Ltda (Venturer) 33.83%; Triunfo Participações e Investimentos S.A. (Venturer) 15.79%	Tropical & Subtropical Dry Broadleaf Forests	6.47	0.1	0.23	0.29	0	0	0	1.28
Rabicho	MMX Mineração e Metálicos S.A. (Owner) 100%	Tropical & Subtropical Dry Broadleaf Forests	6.47	0.12	0.23	0.15	0	0	0	1.28
Corumba	Vale S.A. (Owner) 100%	Tropical & Subtropical Dry Broadleaf Forests	6.47	0.13	0.23	0.12	0	0	0	1.28
N4W	Vale S.A. (Owner) 100%	Tropical & Subtropical Moist Broadleaf Forests	6.46	0.11	0.01	0.22	0.04	0.01	0.68	1.28
N4E	Vale S.A. (Owner) 100%	Tropical & Subtropical Moist Broadleaf Forests	6.46	0.11	0.01	0.17	0.04	0.01	0.68	1.28
Cajati	Mosaic Company (Owner) 100%	Tropical & Subtropical Moist Broadleaf Forests	6.46	0.14	0.17	0.11	0	0	0	1.28
Fabrica Nova	Vale S.A. (Owner) 100%	Tropical & Subtropical Grasslands, Savannas & Shrublands	6.45	0.12	0.16	0.17	0	0	0	1.28
Southeastern System	Vale S.A. (Owner) 100%	Tropical & Subtropical Grasslands, Savannas & Shrublands	6.45	0.13	0.16	0.1	0	0	0	1.28
Canastra	Qualimarcas Comercio E Exportacao de Cereai (Venturer); Socios Quotistas de Mineracao do Sul Ltda (Venturer)	Tropical & Subtropical Grasslands, Savannas & Shrublands	6.45	0.12	0.01	0	0	0	0.68	1.28
Northern System	Vale S.A. (Owner) 100%	Tropical & Subtropical Moist Broadleaf Forests	6.45	0.11	0	0.01	0.05	0.01	0.68	1.28
Timbopeba	Vale S.A. (Owner) 100%	Tropical & Subtropical Grasslands, Savannas & Shrublands	6.45	0.12	0.16	0.01	0	0	0	1.28
Cacapava do Sul	Nexa Resources S.A. (Optionor) 75%; IAMGOLD Corporation (Optionee) 25%	Tropical & Subtropical Grasslands, Savannas & Shrublands	6.43	0.1	0.11	0.01	0	0	0	1.28
Passagem	Cia Minas da Passagem (Owner) 100%	Tropical & Subtropical Moist Broadleaf Forests	6.43	0.14	0.01	0.01	0.18	0.03	0	1.28
Conta Historia	Vale S.A. (Owner) 100%	Tropical & Subtropical Grasslands, Savannas & Shrublands	6.43	0.13	0	0	0	0	0.2	1.28
Candiota	Cia Riograndense de Mineracao (Owner) 100%	Tropical & Subtropical Grasslands, Savannas & Shrublands	6.42	0.12	0.01	0.09	0	0	0	1.28
Mariana	Vale S.A. (Owner) 100%	Tropical & Subtropical Grasslands, Savannas & Shrublands	6.42	0.13	0	0.05	0	0	0	1.28
Urucum	Vale S.A. (Owner) 100%	Flooded Grasslands & Savannas	6.42	0.12	0	0.06	0	0	0	1.28

DIGGING DEEPER INTO THE DATA

The high-level assessment shows that the three case study mines are fairly highly ranked, with a higher score suggesting a higher likelihood of an ‘environmental issue’, and with Aurizona performing slightly worse than the other two on its initial high level environmental impact scoring. To improve insights, we need to dig into the data.

ISSUES TO CONSIDER

TEMPORAL AND WIDER CONTEXT

When considering Protected Areas, or other area designations, it’s useful to consider if commercial activity predates the designation in question, or has an exception, or is legally allowed to occur within that area. For example, some states allow various forms of extractive activity within certain protected areas, and some designations, such as KBAs, have no legal standing. One way to consider this, if available, is to use the attributes of the datasets, such as dates of designation of the protected area and dates of the mining claim. If this is not possible, additional research may be required to fill data gaps.

When we look at the three example mines (Figure 13), the mines predate the PAs. Here, a complication occurs: mines go through long development phases, and the majority of their environmental impact may have occurred under different ownership. Unpicking when the impact occurred and who was the responsible owner at the time can be complex. It may be initially sufficient for most high-level ESG purposes simply to identify when the current owners took control and if that predates any key area designations (Figure 13).

Mine Name	Est. Project start (Est. Current owner)	PA/s Dates	IUCN Category	KBA Dates
Aurizona	1978 (2019)	1991 and 1993	V, Ramsar Site	2009
Capanema	1983 (2014)	1994	V	2009
Northern System	1986 (1986)	1998	VI	2009

Figure 13 - Table showing the dates of designation of protected areas the mines overlap with against estimated project start dates of the mines.

Temporal context is also vital for establishing the initial impact of an asset. If an observational data layer is applied after the development of the asset, the scores will be biased by the prior impact of the asset itself (Figure 11, 12). For example, a forest loss metric 10 years after the development of the mine is likely to be low or zero for the mine site, as the more recent dataset will not detect any change in forest cover for the site as it has long been deforested. Subsequently, the impact of a mine needs to be considered across time; this is made more challenging by a lack of consistent observational historic data to draw upon. In some cases, this is impossible with mines or assets predating the archive satellite imagery records (mid-1980s). In these cases, and others, it may be possible by considering surrounding vegetation to predict the prior state of the area and estimate the site’s initial impact. However, if resources are available, the growth of a mine can often be calculated with remote sensing to show expansion over time (See Page 36).

THE NEED TO DIFFERENTIATE WITHIN OBSERVATIONAL DATASETS

It is important to differentiate variables within observational datasets to better understand initial and ongoing impacts. For example, no two protected areas, indigenous areas, key biodiversity areas, etc., are equal. Some are high status, some are pristine, others may be heavily degraded. An asset overlap with a conservation area should be considered by the site’s specific values, rather than as a binary value. Within the three case study mines, the protected areas they overlap have differing IUCN management categories and designations: IUCN Cat. V[59] or VI[60], and one of them is a Ramsar site, a wetland of international importance (Figure 13). ESG analysts might wish to use these or other relevant designation as a useful metric to highlight operations with potentially higher risk and impact.

However, beyond simple site attributes, it is vital to consider each site's wider values. Is the protected area already heavily degraded? Does it have a high endangered species presence? Does it contain multiple other commercial operations? Does it have pristine forest? High levels of deforestation? Do conservation NGOs have a presence within the site? Does the site have a high international internet saliency? Is the site important for tourism? We provide no methodology for how to consider this, but it is possible to weigh the values of individual polygons, such as PAs or KBAs, against hundreds of other variables,[61] to provide more in-depth insights as to the likelihood that operations within a site present a significant and immediate reputational risk and to help aid in scaling the probable environmental impact at a high level. The three case study mines, for example, each overlap with different PAs, each with a different number of IUCN endangered species present (Table 14).

Mine Name	IUCN Red Listed species with PA (All / Least Concern / Near Threatened + Vulnerable + Endangered + Critically Endangered)	WWF CI PA Screening Score
Aurizona	890 / 794 / 96	0.34
Capanema	778 / 714 / 64	0.29
Northern System	719 / 671 / 48	0.27

Figure 14 – Table showing additional information about the endangered species likely to be present in the PAs overlapped by the three mines to improve differentiation of possible impacts.[62]

Aurizona, which is on a Ramsar site on the coast, faces the highest scores, as could be expected; but the two other sites also face regionally and internationally high scores, as would be expected in tropical regions, which will naturally have a high global level of biodiversity.

Of course, mining projects bordering or outside PAs, KBAs or other key designations can still cause significant damage to the natural world. Regardless of the situation, any commercial operation outside key designations does not necessarily legitimize or negate the biodiversity impact or reputational and material risks of the activity. Every site needs to be considered for its impact. Key area designation assessments as above provide a useful data point, but they should always be considered in connection with other geospatial and traditional ESG data points to build out a wider high-level understanding of the site's impact.

SECONDARY ENVIRONMENTAL IMPACTS

Secondary impacts are often tricky to capture and require detailed and tailored methods. For example, many mines in Brazil have opened previously intact forest to wider secondary exploitation by building roads to build new mines. This issue can be captured in a geospatial layer like forest fragmentation, but this needs to be correctly applied over historic years, for which there may not be open data.

SECTOR SPECIFIC APPROACHES

The various complications highlighted above show the strong need to develop sector-specific geospatial methods if actors wish to gain maximum insight and more precisely attribute environmental impact. Within this example, with slightly more advanced manipulation of the data, it is possible to integrate the attributes of the mining asset data. For example, data defining the mine's pit type (open or closed), commodity type (i.e. gold, iron ore), production status, work history and tailings volume can be used to differentiate mines, separating different types of mines to assign different impact weightings more precisely.

Beyond this, it is possible to build highly complex models utilizing all the various data and associated attributes, to consider assets over time, secondary impacts and near-real-time changes. For example, mining sites with tailing dams located in areas historically exposed to extreme rain events are potentially more suspectable to risk of tailing dam failure. This risk can be better triangulated using other variables, such as elevation of the dam, dam size, work history, surrounding urban population, water height, habitat types, water dynamics, wildfires and even dynamic weather data to determine at a high level those assets, and those companies, most exposed.

ONGOING IMPACTS

Here we have shown the outlines of a geospatial ESG approach, focusing on defining the initial impacts of mines with the open data portfolio. Ongoing impacts (e.g. daily methane pollution) can in some cases be monitored week by week via remote sensing products. Such monitoring is by its very nature sector-specific – for example, marine oil spill detection and CH_4 emissions are more likely to be relevant to the oil and gas sector and certain types of mining than to, say, cotton production. Within mining, some remote sensing products provide a means for ongoing monitoring, where, for example, forest loss and land cover change datasets help to show if the mine is expanding. Whilst other datasets, such as infra-red heat profile, and depth and extent of an open pit, might be useful to predict CH_2 emissions and productivity. Commonly these products are provided by the commercial space, although some are within the open domain. In the future, additional ground data sources, such as in-situ smart meters or landscape audio, are likely to play a clear role in defining insight into an asset's ongoing environmental impacts and stresses.

SUPPLY CHAIN IMPACTS

The emerging world of geospatial ESG is currently limited by which sectors have robust asset datasets. Currently, most are primary industries: mining, oil and gas, power plants, fishing, shipping, cement, etc., whose environmental impact is primarily linked to actual operations. Secondary and higher industries, whose impact is mostly in the supply chains, will more pressingly need robust supply chain assessments. Naturally, this is only possible where supply chain data is available,[63] which currently is rarely the case. To resolve this, we commonly see regional 'impact' or 'risk' averages developed, where a company might not know which exact area the product was sourced from, but they know the state or region. Thus, we can provide an averaged regional risk or any number of regional values to provide some level of insight into that supply chain. This is, of course, limited, but until we achieve greater transparency around supply chains, geospatial ESG insight and applicability will remain constrained. In the next case study, we explore the value of this regional averaged approach (See Case Study 2).

Within this mining example, we could, for example, define every power plant in Brazil, its type, and output, and then create renewables vs. non-renewables ratios per municipality as a proxy for the likely renewable power usage of mines within Brazil. This value and others can then be modelled against mining production, commodity type, etc. to give insights into the mine's production versus its high-level environmental impact efficiency.

CONCLUDING REMARKS

The approach outlined here is relatively simplistic. It is possible to develop the approach in far greater detail, considering the exact footprint of the asset against a more sector specific model, to better define the initial environmental impact and then the ongoing impact. The idea here is not to promote an exact method but to outline the basics of the approach in order to illustrate the concept of geospatial ESG. Discussing how various factors need to be considered, it becomes apparent that off-the-shelf data products often need to be refined. Yet even with this approach and with currently available data, insights are possible which arguably are useful to consider alongside traditional ESG data portfolios.

In the next section, we outline examples of additional sector specific insights that are possible via commercial remote sensing providers and show how more refined insights are possible.

BOX THREE

KAYRROS - EXAMPLES OF INSIGHTS VIA COMMERCIAL SATELLITE REMOTE SENSING PRODUCTS

Authors: Claire Bonfils-Bierer, Product Manager - Kayrros and Alexandre d'Aspremont, Chief scientist - Kayrros

To illustrate additional remote sensing insights that are possible and that can be integrated to refine geospatial ESG approaches, we look at one of the case study mines, Northern System in Brazil. Specifically, we explore production, mined areas and removed material based on a combination of 3D Reconstruction, SAR Change Detection Index and Land Cover Multispectral Analysis. The goal is to detect changes in production rates as well as expansion of the mine activities and impacts on the surrounding ecosystem.

CASE STUDY LOCATION

The results below have been produced for the iron ore mining complex, Northern System in Brazil. Depending on the analysis, the whole mine complex of Northern System highlighted in white on the picture below or a reduced area in the south east highlighted in blue on the picture has been covered.

A series of analyses from mid-resolution to high-resolution have been conducted to track how the industrial activity of the mine evolved and has impacted the environment and the land.

Figure 15 – Image showing the study areas considered.

STEREOSCOPIC 3D MODEL

We built a high-resolution 3D model of a sub-area by combining image processing and machine learning technologies.[64]

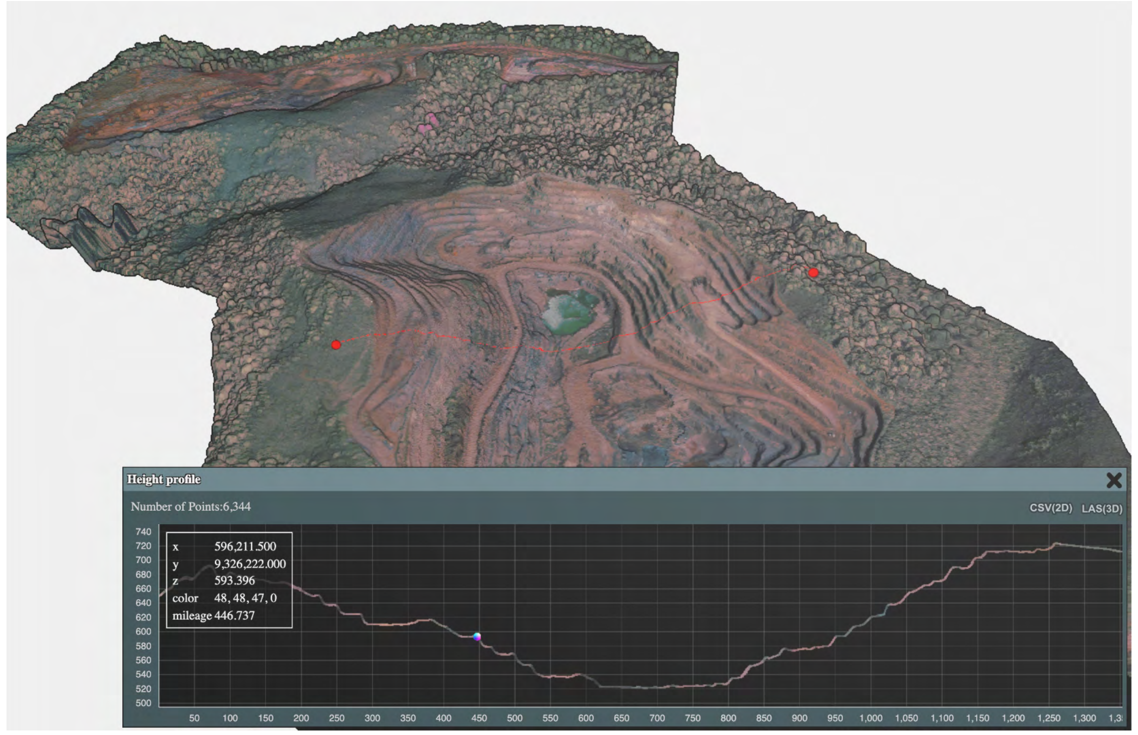


Figure 16
Digital reconstruction of a Mine Northern System sub-area on July 16, 2020, derived from the SkySat constellation.
(Sources: Kayrros Analysis powered by Planet.)

After tasking a satellite to take a pair of stereo images— multiple images pointed to the same spot on Earth from different angles— we applied proprietary algorithms to transform this set of images into a 3D model, generating a digital topographical snapshot.

This technology enables us to produce digital reconstructions of any remote location worldwide, and can be used as a critical tool to assess the volume of material removed from mines or the forest heights around it, for example.

Complementary to the 3D rendering made possible by high-resolution imagery, medium resolution multi-spectral images— combined with deep learning algorithms— classify the land in near-realtime (with access to historical data).

By using machine learning algorithms to detect different types of land cover, we can then differentiate forest areas from other types of areas, including mined areas (as shown below). This allows us to track forest cover levels in addition to the land occupied by the mine itself across time, as shown in Figure 17.

Processing historical Landsat multi-spectral images enabled us to track the land surrounding the mine dating back to 1984. This allowed us to derive a comprehensive overview of the mine's expansion over a long period of time, complementing the near-real-time coverage that we have today.

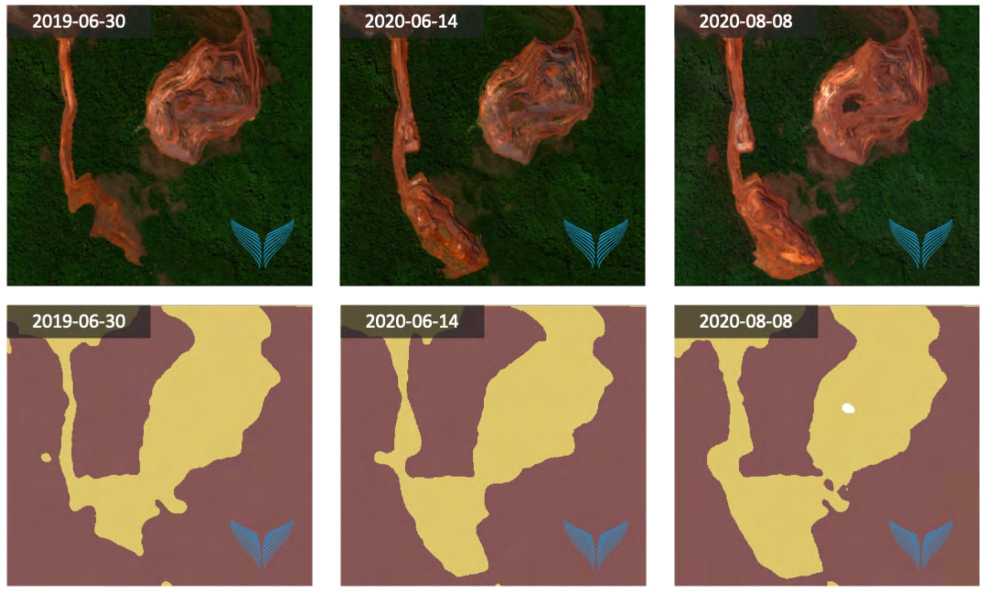


Figure 17 – Top: Optical Sentinel-2 images covering the Northern System Mine's sub-area on three different dates. Bottom: Land cover classification mask associated with the three different dates; forest areas are shown in brown, water areas in white and other (including mining) areas are shown in yellow. The forest surfaces evolve, as shown in the third row.

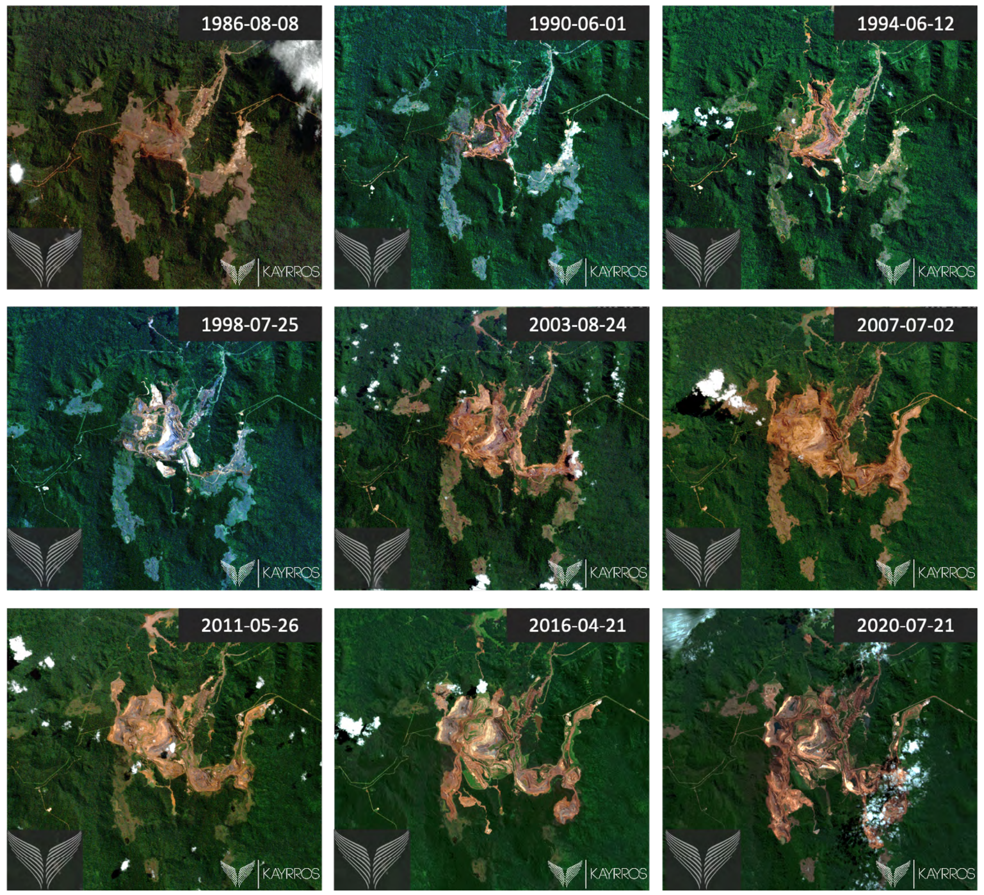


Figure 18 – Sample of Landsat-4 and Landsat-8 images on the Northern System Mine taken since 1986. (Source: Kayrros Analysis, Landsat-4 to Landsat-8 images, courtesy of the U.S. Geological Survey.)

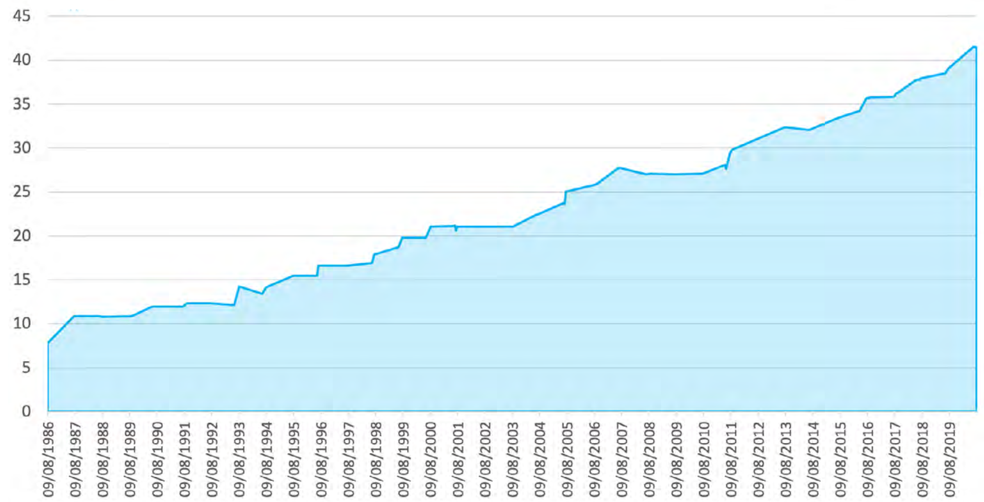


Figure 19

Evolution of the Northern System Mine's surface area from 1986 to 2020.

(Source: Kayrros Analysis, Landsat-4 to Landsat-8 images, courtesy of the U.S. Geological Survey.)

We generated the Kayrros Mine Activity Index to illustrate the impact of mining activity on the ecosystem.

To tackle this, we built a quantitative index to track production in full systems, derived fromapplying change-detection algorithms onto Sentinel-1 Synthetic Aperture Radar (SAR) images.

Then, we built coherence maps based on interferometric principles from the monitored mine; in simpler terms, images of the mine in which each pixel's value varies from 0 to 1, which represents to what degree the structure of the field changed between two consecutive dates. The change index over the whole area is then derived from aggregating over pixels and normalizing.

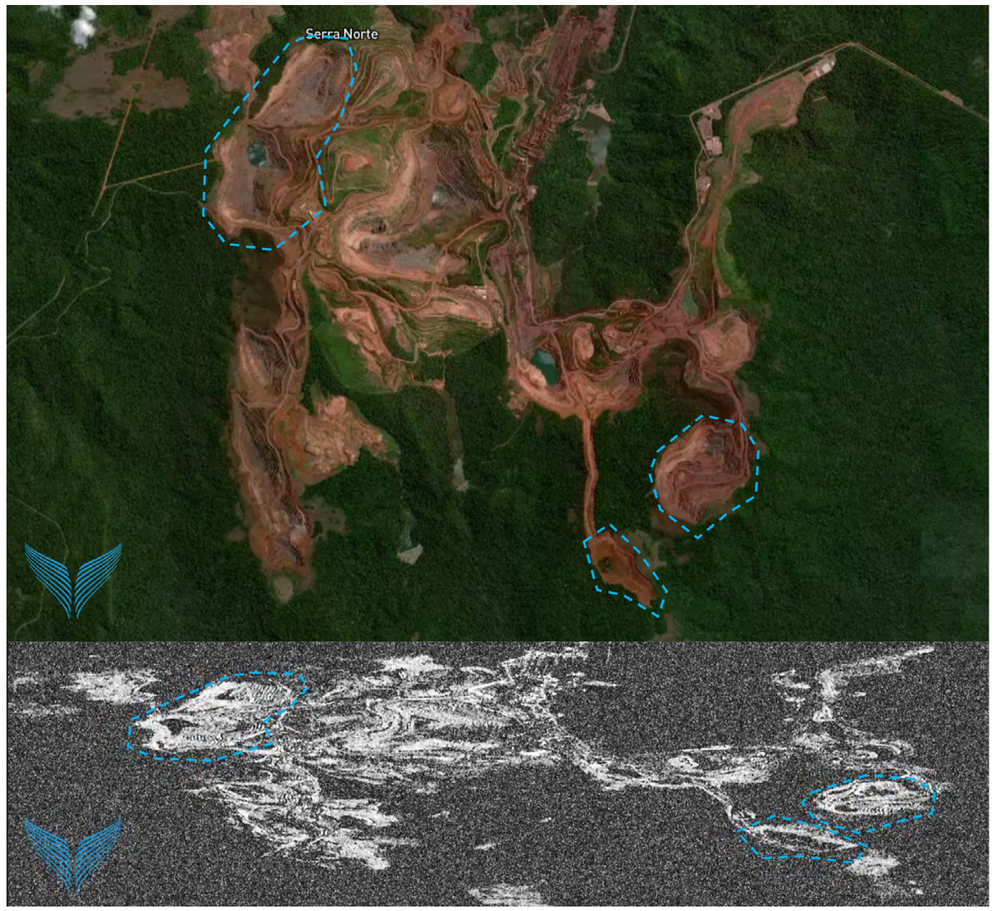


Figure 20

Top: Overview of the Northern System Mine and mapping of its sub-areas.

Bottom: SAR coherence map produced using a Sentinel-1 image taken on September 5, 2020. The blue polygons show a sample of the pits. Dark pixels indicate important changes since the last acquisition.

(Sources: Kayrros analysis; contains modified Copernicus data (2018–2020).)

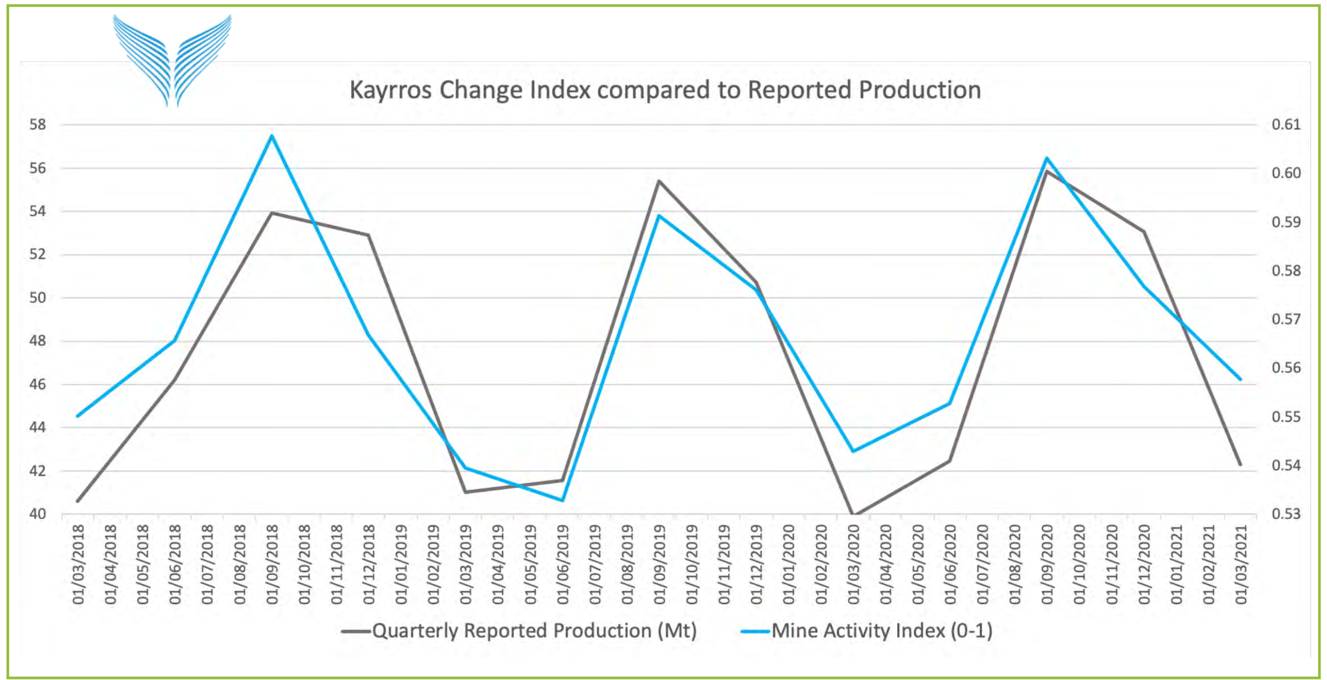


Figure 21
Quarterly Kayrros Change Index vs. Reported Production (MT). The analysis shows the correlation between the index generated and actual production.

(Sources: Kayrros analysis, contains modified Copernicus data (2018–2020).)

CONCLUSION

Data fusion is key to deriving a comprehensive view of mines, both historically and in near-real-time. Remote sensing sources and sensors— such as multi-spectral, stereo and radar— offer a wide range of signals at different spatial and temporal scales. This provides direct insights on both industrial activity and its environmental footprint.

BOX FOUR

ENVERUS – SATELLITE INSIGHTS INTO THE OIL AND GAS SECTOR

Authors: Nick Volkmer, Vice President, ESG – Enverus and Jingwen Zheng, Lead Data Scientist – Enverus

Satellites are bringing unprecedented oversight into global oil and gas operations. Investors today are able to monitor flaring levels, methane leakage rates and development practices from a suite of satellites that is set to expand in the coming years. The visibility is welcomed by institutions looking to align capital with responsible development practices and by producers that want to showcase superior operations, particularly those in North America and Europe.

Take Colorado, for example, where the Denver–Julesburg (DJ) Basin sits near the Denver metropolitan area. As the city has grown, neighbourhoods often overlap with oil and gas operations. Satellite imagery and telemetry data allow us to understand how operators are changing development practices in response. Since 2018, DJ operators have increased average land efficiencies, or the amount of hydrocarbons recovered per surface acre disturbed, by about 40%, largely by drilling more wells with longer horizontal lengths (or laterals) from a single surface location (Figure 22). Satellites paired with reported data sets enable precise yet broad monitoring of these field-level activities. Similar workflows are being developed to analyse flaring and methane rates across North American operations and will be available in the ESG Analytics module in Enverus' Prism platform.

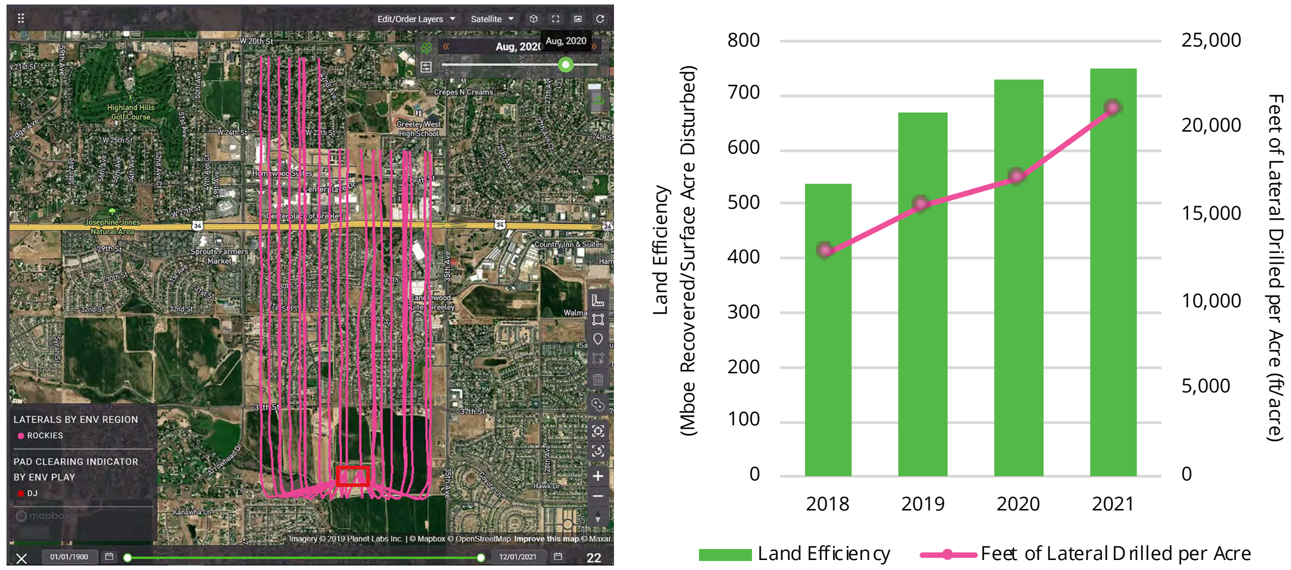


Figure 22
(Left) Satellite imagery shows an algorithmically detected well pad location (red box) and subsurface well lateral locations (pink lines) for a pad in the DJ basin. (Right) The primary y-axis shows the average DJ basin land efficiency calculated as the sum of the estimated ultimate recovery (EUR) of wells on a pad over a 30-year production profile over surface acres disturbed, and the secondary y-axis shows feet of lateral drilled per surface acre disturbed.

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CASE STUDY TWO

COMPANY LEVEL ASSESSMENT – SOFT COMMODITIES IN BRAZIL – TRASE

Author: Helen Bellfield, Policy Director (Trase Lead) – Global Canopy

In many cases it isn't possible to identify where specific products are produced. In these situations, without a defined asset location, what insights can a geospatial ESG approach bring to the table? One solution is to consider data at a regional level, as conducted by the Trase tool, which provides insights into the deforestation risk within soft commodity supply chains.

The production and trade of soft commodities, including soy, beef and palm oil, is associated with the conversion and degradation of tropical forests and native vegetation. A number of banks, investors and companies have made voluntary commitments to remove deforestation from their portfolios and supply chains, and in November 2021 the EU Commission published a proposed regulation to prohibit the placing of products and commodities associated with deforestation and forest degradation on the EU market.

Assessing the deforestation risks associated with a specific company's supply chains and sourcing requires mapping products back to production regions. This presents a significant challenge due to issues that include long supply chains with indirect suppliers; aggregation and bulking of commodities such as palm oil, soy and maize; and the size of the supply base.

This case study illustrates an approach pioneered by Trase to use publicly available data to map soft commodity supply chains at scale to connect per shipment trade data to subnational sourcing regions. In the case of Brazil's soy exports, Trase maps 100 million tonnes of soy that was exported in 2018 by 300 trading companies and estimates that these exports were associated with 50,000 ha of soy deforestation risk.

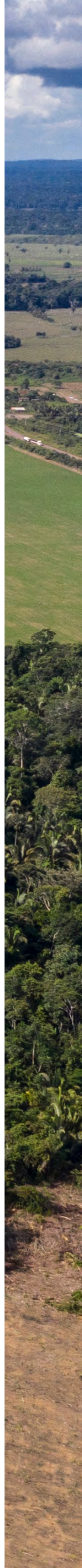
METHODS

1. Mapping soy supply chains

Trase links Brazilian soy exports to sub-national municipalities of production via processing (e.g. crushing facilities, refineries) and storage facilities (e.g. silos), as well as deforestation impacts in these municipalities. First, we link individual export shipments back to municipality locations of taxation considering both the trader (with tax information) and the Brazilian state of production corresponding to the farms, silos, crushing facilities or wholesale retailing (i.e. trader assets) linked to the export shipment. Second, we link these assets with the municipalities of production where the soy was most likely produced (not to individual farms except in cases where we can make a direct link), through a minimum cost flow analysis using linear programming. This approach is optimised using the combination of trader assets, domestic consumption and export demand for soybeans, and transportation costs to identify the most likely municipality of production supplying these silos and crushing facilities. Exports are then aggregated annually and by trading company to provide an annual sourcing map by trader. Please see more information here.

2. Assessing soy deforestation

In each soy producing municipality, Trase assesses recent soy deforestation. This is calculated by comparing the area of production associated with a specific harvest and export of soy to recent deforestation that has directly contributed to the production of that harvest. We estimate this based on the time it can take between the initial deforestation of an area of land and the processes of acquiring, preparing and selling the land before soy is typically planted. This is estimated to be five years for soy in Brazil. In addition to this 'allocation period', we also consider a one-year 'lag period' representing the minimum time needed between a deforestation event and the harvest of soy.



To derive direct deforestation associated with soybean production within the five-year allocation period, we:

- Put together an annual deforestation increment map (30m resolution) combining Amazon, Cerrado, Atlantic Forest and Pantanal deforestation. In cases where data is not available annually (for example, for earlier years of the Cerrado time series, and for the Atlantic Forest), we obtain the annual mean deforestation by dividing per-pixel deforestation by the timeframe between two deforestation datasets. Note this covers primary and not secondary deforestation.
- We process annual maps of soy extent (30m resolution) to remove fragments less than 20 hectares based on IBGE data on soy farms.
- We then compare total soy coverage in year y (e.g. 2019) to historical deforestation increment maps over the preceding five-year period (2014–2018 inclusive) as illustrated in Figure 23.
- Finally, we aggregate this to the municipality level.

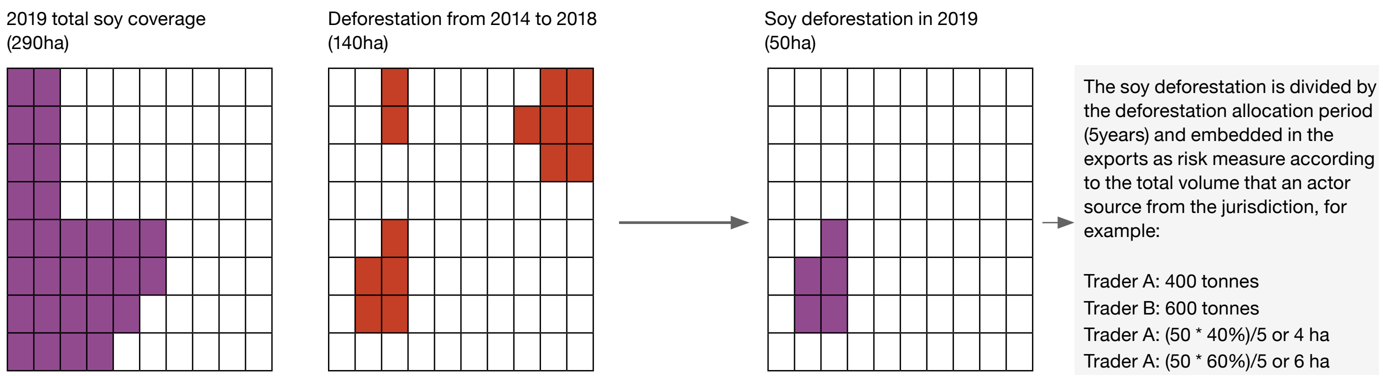


Figure 23 – To calculate soy deforestation in 2019, we overlay soy production in 2019 with deforestation increment maps from 2014–2018 inclusive to identify soy deforestation.

3. Assessing trader's soy deforestation risk

We connect soy deforestation to soy exports to create a measure of soy deforestation risk associated with each trader's supply chain. To estimate soy deforestation risk associated with exports, the estimated share of soy that is purchased by each trader or for each producing municipality (step 1) and assign soy deforestation in each municipality (step 2) proportionally to each trader. For example, if a trader buys 20% of a municipality's soy in a given year, it gets 20% of the municipality's soy deforestation. It is important to emphasise that this measure estimates the risk that a commodity trader is exposed to deforestation in its supply chain, based on the jurisdictions it is sourcing from.

4. Aggregating soy deforestation risk to parent companies

In many cases, parent companies include different subsidiaries that are exporting and importing soy from Brazil. For example, Cargill Brazil exports soy, and Cargill France imports soy. This means that subsidiaries within the same company may trade with each other. Therefore, in aggregating soy deforestation risk at the parent company level, we need to avoid double counting the risk where one subsidiary exports volumes imported by another subsidiary. We calculate the total risk of parent companies as the total soy deforestation risk associated with all the company's subsidiaries' exports plus the total soy deforestation risk from all the company's subsidiaries' imports, excluding imports from the company's own subsidiaries (as these have been accounted for under exports).

5. Translating data into ESG metrics

Red, amber and green flags are used to highlight areas of deforestation risk exposure for each trading company, These include the following environmental metrics:

- The company is one of the top 10 exporters of Brazilian soy
- Soy deforestation risk (ha)
- Relative soy deforestation risk (ha/1000 tonnes)
- The company sources from high risk regions (e.g. the Matopiba region, a current soy deforestation frontier)
- The company sources from top quartile of municipalities with the highest soy deforestation

DATA SOURCES

Supply chain mapping

- Per shipment data
- Asset ownership and related activities – e.g. soy crushing: CNPJ, ABIOVE
- Soy production data: IBGE

See Brazilian soy methods documents for more information.

Soy deforestation risk

- Soy crop extent (30m resolution): Global Land Analysis & Discovery (GLAD) – University of Maryland
- Deforestation (30m resolution):
  - INPE Prodes Amazon (1998–2019 annual)
  - INPE Prodes Cerrado (2000–2012 every two years; 201–-2019 annual)
  - SOS – Mata Atlantica (2000–2005 (every six years); 2006–2008 (every three years); 2008–2010 (every two years); 2011–2016 (annual)
  - SOS – Pantanal (2003–2008 (every six years); 2009–2016 (every two years) 2017 (annual)

Note that recently more comprehensive data on deforestation that cover the entire country has become available from MapBiomas that will provide a single source of data negating the need to patch together multiple sources.

See Commodity deforestation and commodity deforestation risk for more information

Company legal hierarchy

- Financial service providers – e.g. Factset, Refinitiv Permid
- Open corporates
- GLEIF
- National Companies House registries including CNPJ

RESULTS

A hundred million tonnes of soy were exported from Brazil in 2018 by 300 trading companies. Trase estimates that these exports were associated with 50,000 ha soy deforestation risk. The trade is highly concentrated, with the four 'ABCD' traders handling 50% of exports. These traders' exports are associated with 43% of soy deforestation risk.

However, depending on their sourcing patterns, these traders have different exposure to soy deforestation risks. Louis Dreyfus accounts for 10% of total exports but only 1% of total soy deforestation risk, because it mainly sources from the south of Brazil where forests were cleared many years ago. In contrast, Bunge trades 16% of exports but accounts for 22% of total soy deforestation risk due to its sourcing regions including the Matopiba region, where soy deforestation is currently happening (Figure 24).

The concentration of risk in a handful of production regions is highlighted by the fact that 50% of soy deforestation risk associated with Brazil's soy exports are from 1% of soy producing municipalities (18 out of 2318 municipalities).

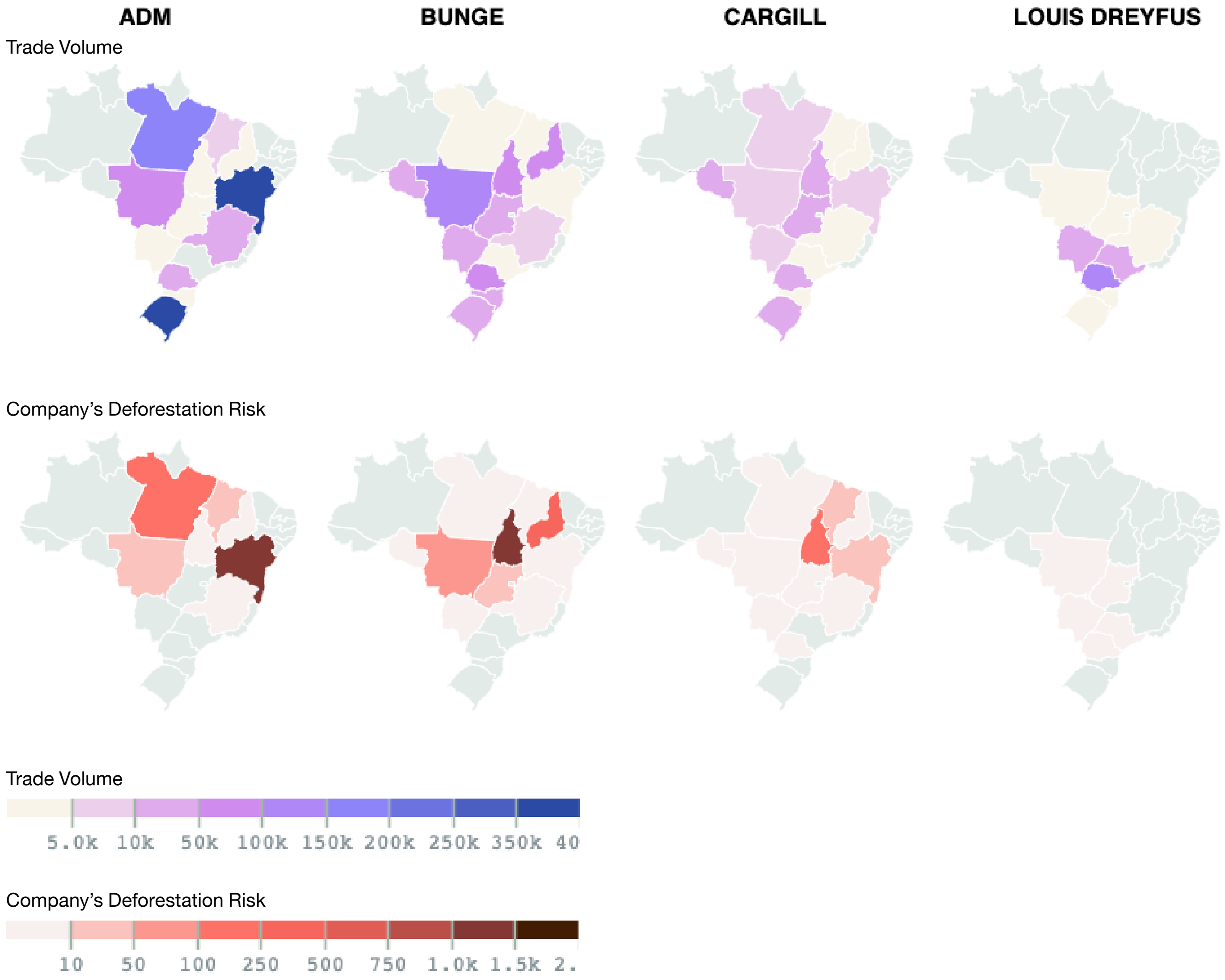


Figure 24
Sourcing map of soy exports in terms of volumes and associated soy deforestation risks of the ABCD soy traders who dominate the trade.

Company	Soy exports in 2018 (million tonnes)	Soy deforestation risk in 2018 (ha)	Sourcing soy from Matopiba (high risk region) in 2018 (million tonnes)	Sourcing from the 6 municipalities that represent the top 25% of soy deforestation risk in 2018 (million tonnes)	Company soy policy (Forest 500)
ADM	11.4	6,474	1.01	0.66	60%
Bunge	15.7	11,197	1.31	0.58	57%
Cargill	12.8	5,432	0.81	0.06	41%
Louis Dreyfus	9.8	493	0	0	46%

Figure 25
Environmental risk metrics for the ABCD traders of Brazilian soy.

LIMITATIONS

Traceability. Soy supply chain traceability gaps remain an important barrier in linking products handled by supply chain companies to soy deforestation impacts. However, Trase demonstrates that it is possible, through utilising existing public datasets, to create a supply chain map that links exports to producing regions and therefore to deforestation impacts in these regions. While this is an important step forward, Trase cannot directly attribute responsibility for deforestation to specific companies, as data on precise sourcing patterns back to individual farms are not publicly available. Among other data sources, Trase uses information publicly disclosed by companies in its supply chain mapping. As company sourcing data becomes more transparent, Trase can adjust its estimates of a company's deforestation risk and reflect demonstratable deforestation-free sourcing being achieved by more progressive companies.

Indirect land use change. Measures of direct soy deforestation only tell part of the story. While the majority of soy expansion in the Brazilian Amazon over the past decade has taken place onto land already cleared for pasture, the overall area of pasture remains more or less unchanged. In other words, as pasture is converted into agricultural land for soy and other crops, forest and savannah are cleared for new pasture. This suggests that soy expansion is indirectly driving deforestation.

Gaps and time-lags in the availability of data. Trase data for Brazilian soy is only currently available for 2018 due to gaps in data availability for more recent years. More broadly, government data is often published with a time lag. While Trase time series data show that sourcing patterns do change over time, they also indicate that such supply chains remain 'sticky' – many of the larger trading companies are vertically integrated and have significant investments in soy silos, crushing facilities and port terminals as well as relationships with farmers, including via the provision of finance and inputs. There is an opportunity to also use this historic data to predict future deforestation risk.

CONCLUSION

Assessing environmental risks associated with soft commodity supply chains requires mapping products back to farms and concessions or at least to sub-national regions of production. While traceability and transparency remain significant barriers to mapping soft commodity supply chains, this case study demonstrates an approach for 1) mapping soy supply chains and 2) connecting supply chains to soy deforestation using publicly available data that already can provide useful insights, such as the high concentration of risks in these supply chains, that can guide investor engagement with clients.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CASE STUDY THREE

SOVEREIGN LEVEL ASSESSMENT – A GEOSPATIAL VIEW ON DROUGHTS AND EMPLOYMENT IN BRAZIL – THE WORLD BANK

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INTRODUCTION

The rapidly growing availability of geospatial data paves the way for better Environmental, Social and Governance (ESG) scores and ultimately, better informed ESG investing.[65] This holds true not only for corporate entities, but also for sovereign nations, which this chapter focuses on. Asset managers, pension funds and other institutional investors are integrating ESG factors into their investment portfolios, which are a major source of capital flows in global financial markets.[66] For example, in 2018, the investment bank J.P. Morgan and the asset manager BlackRock launched the JESG index, which incorporates ESG considerations into existing flagship benchmark indices that track government bonds in emerging markets (EM).[67] As a report by the International Monetary Fund finds, investments that track benchmark indices have grown rapidly in EM bond markets, standing at around US$ 300 billion in 2019.[68]

Sovereign ESG scores, which lay the foundation for the operationalization of ESG investing in sovereign fixed-income markets, are not without controversy as two recent World Bank reports document.[69] For example, ESG score providers generally agree on what constitutes a good sovereign performance for Governance and Social issues. However, this is driven by the ingrained income bias, which refers to the fact that 90 percent of sovereign ESG scores can be explained by a country's national income.[70] In comparison, there is considerably less agreement on what constitutes a good score on the Environment pillar. This is due to disagreements on what "good" performance is on a conceptual level, but also due to data gaps, out-of-date statistics, and heterogeneous reporting standards, which often force providers to fill in and estimate missing values. Moreover, even if records are available on the national level, corresponding subnational data rarely exists. Comparability across countries depends heavily on capabilities of national statistical offices.[71] Geospatial data presents a promising solution with global, consistent, and highly frequent coverage that is objective in nature.

The two World Bank reports also argue that better data measurement alone is not sufficient. Even though geospatial data helps better assess the environmental materiality of an indicator, such as better measurements of deforestation, desertification, or coral bleaching, it does not directly translate into economic materiality, e.g., economic output, employment figures, which in turn influences financial materiality, e.g., risk management or investment incentives.[72] It is therefore crucial to process and convert geospatial data into economically meaningful numbers. This does not only refer to the units or the aggregation level of the data, as we will discuss shortly, but also to the very interpretation of the statistics.

This chapter showcases how to establish an empirical link between environmental and economic for the case of precipitation anomalies in Brazil's regional economies. To estimate the strength of this link, we use the local projection methodology that has been widely used to understand how economies respond to events, such as economic policy changes, market disruptions or natural disasters. While it would be interesting to examine the link with financial materiality, we leave this to future research. In the following, we first describe how geospatial data helps us better quantify the environmental materiality of droughts before we move on to estimate its link with the economy.

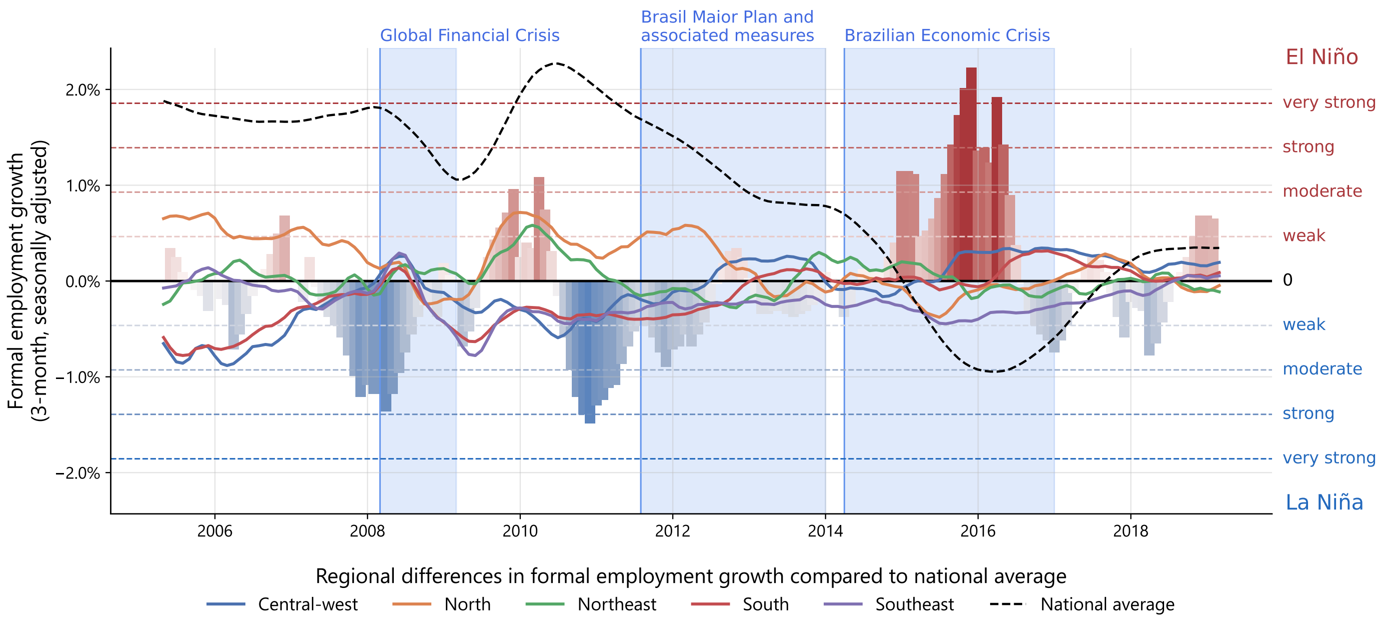


Figure 26
Growth in Brazil's regional formal employment and the El Niño–Southern Oscillation

Quarterly formal employment growth in each of the five Brazilian regions (left axis, colored lines) and the national average (left axis, black dashed line) are plotted against the backdrop of the Oceanic Niño Index (right axis, red and blue bars). Visual inspection may lead to the conclusion that the El Niño was chiefly responsible for the 2015/16 downturn. However, it is more likely that its role was aggravating the effects of the end of the commodity supercycle and the corruption scandal ("Lava Jato"). This warrants a more rigorous investigation.

MEASURING PRECIPITATION ANOMALIES

The Standardized Precipitation Indicator (SPI) was introduced by McKee, Doesken, and Kleist (1993) to detect anomalies in precipitation patterns, such as unusually wet or dry conditions. The geospatial indicator used in this study is calculated by the Copernicus European Drought Observatory on a monthly frequency and with a spatial resolution of 1 decimal degree (around 110km, see Figure 27). SPIs are calculated over a specific accumulation period (e.g., 1, 3, 6 or 12 months) as deviations from the expected historical mean. Concretely, a high SPI-1 value in January indicates that it deviates strongly from historical rainfall values in January in previous years. SPI-1 to SPI-3 (1 to 3 months), are short-term measures that detect reduced soil moisture which could worsen crop health. SPI-3 to SPI-6 encompass entire growing or harvesting seasons where seasonal droughts can occur. SPI-12 represents an extended accumulation period and lower values could indicate reduced stream flow and water reservoirs. It is important to consider and compare different accumulation horizons, since a shorter-term drought picked up by the SPI-3 indicator may in fact be part of a longer drought that is reflected by SPI-12.[73]

Droughts are a complex phenomenon that no single indicator can fully explain. Accounting for local conditions, such as forest cover, irrigation systems or human settlements, and other hydrological and meteorological indicators is necessary to accurately characterize floods and droughts.[74] In this study we focus solely on SPI and leave a more in-depth treatment for future work.

This rich geospatial data source by itself, however, cannot be directly used to answer economic questions, where researchers are used to deal with tabulated time series or cross-sectional records. We therefore translate the SPI data from the geospatial format into a tabular format that aggregates observations onto the state level. This paves the way for statistical models, which we employ to assess how unusually wet or dry weather conditions affect Brazil's regional employment patterns.

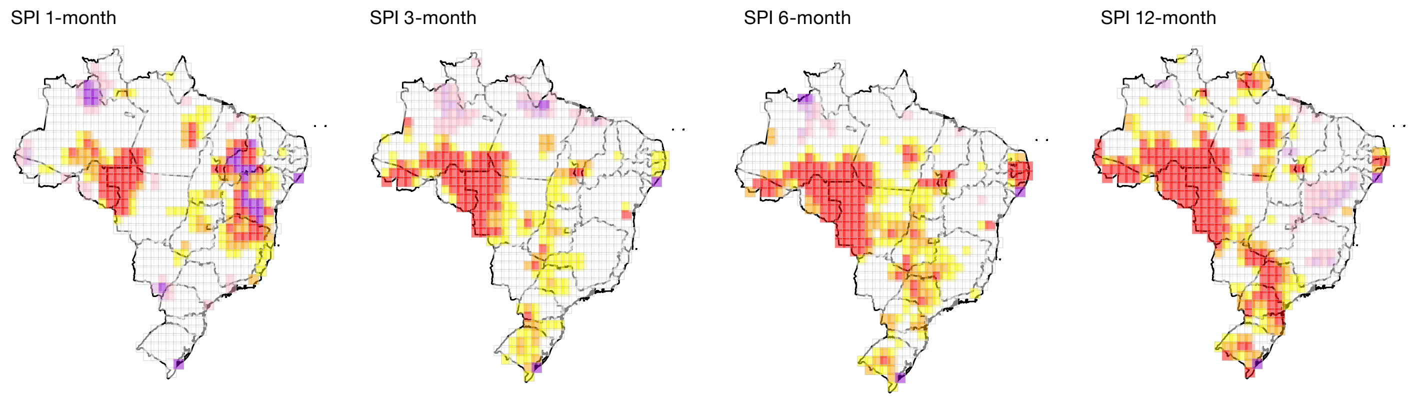


Figure 27
Standardized Precipitation Indicator (SPI) over 1-, 3-, 6- and 12-month horizons.

Values depict the situation in December 2020.
Each square represents 1 decimal degree (around 110km)

CASE STUDY

The World Bank classifies Brazil as highly vulnerable to hydrological and meteorological disasters. Between 1900 and 2016, Brazil experienced economic losses of more than $US 6.1 billion due to flash flood and riverine flood damages. In comparison, heavy and prolonged droughts affected the livelihoods of almost 80 million people and caused $US 111.2 billion in total damages. These events are expected to increase both in frequency and severity in the future.[75]

At the same time, weather variation during and outside of El Niño and La Niña periods have profound effects on the Brazilian agricultural sector (Cirino et al. (2015)). Figure 26 plots the Oceanic Niño Index against the quarterly formal employment growth in each of the five regions of Brazil. The black dashed line depicts growth on the national level, whose trajectory was shaped by major economic events. The coloured lines isolate the region-specific developments in formal employment by calculating the difference between regional and national employment growth. A visual inspection of the figure may suggest some relationship between the El Niño–Southern Oscillation (ENSO) and regional growth figures. One might be tempted to conclude that the El Niño was chiefly responsible for the 2015/16 downturn. However, it is more likely that its role was aggravating the effects of the end of the commodity supercycle and the corruption scandal ("Lava Jato").

SOCIAL CONSEQUENCES OF DROUGHTS

Aside from the economic consequences of droughts, for instance through the agricultural sector by harming plant and livestock productivity, they also affect "[…] public water supply, energy production, waterborne transportation, tourism, human health, biodiversity and natural ecosystems", as described by a recent special report of the United Nations.[76] This is supported by findings in the literature, such as Rocha and Soares (2015), who wrote that early life health is determined by water scarcity and that droughts are "robustly correlated with higher infant mortality, lower birth weight, and shorter gestation periods." Moreover, the same UN report also emphasizes the social consequences, since "droughts may affect men and women differently, and their impacts often amplify existing structural inequalities across social groups, ages or other demographic categories." Indeed, both floods and droughts hurt small rural farmers and poor urban residents, who have limited means to respond to such disasters. Branco and Feres (2018) examined one of the possible responses to weather shocks and found that droughts have an immediate, negative effect on rural household income and thereby incentivize households to take up a secondary job, an effect they found to be stronger in poorer municipalities in the Brazilian Northeast.

DATA

In this case study we demonstrate how geospatial data helps us gain a better understanding of this complex issue. We focus on the regional economies of Brazil's federal units rather than on the federal economy. This level of granularity preserves the heterogeneity between states and allows us to make better use of the geospatial data. Alternatively, the data would have also allowed for the analysis to be conducted on the municipal level. However, our main variable of interest, monthly formal employment growth, is only collected for the state level.

Our dataset starts in mid-2004 and ends in 2021 with a monthly frequency for the 27 federal units. Environmental data is obtained from the European Drought Observatory and the formal employment indicator is retrieved from the Central Bank of Brazil (BCB) and the Brazilian Institute of Geography and Statistics (IBGE). Land use and land cover data is obtained from Souza et al. (2020).

RAINFALL ANOMALIES AND FORMAL EMPLOYMENT

Formal employment growth does not respond to rainfall anomalies in a uniform way. Whether and how much regional economies react to periods of wet or dry weather depends on the federal unit at hand, how long the anomaly persists and when it occurs. For example, does a short drought affect employment growth differently than an extended drought? The response graphs, as described in Figure 28, answer this type of questions.[77] After the accumulation periods of different durations ends, the solid lines show how the effect changes over different response horizons from the immediate, contemporaneous effect up to a year after the event. The effects are estimated using local projection methods (LPM), which are a widely used methodology to estimate the effect of an event on an economy (Jordà, 2005). Events can for example be natural disasters (Dieppe, Celik, and Okuno, 2020; Regelink et al., 2022) or new economic policies (Jordà, Schularick, and Taylor, 2020). A main benefit of LPMs is that they are lightweight and robust to misspecifications. The panel version employed here also accounts for heterogeneities across federal units, such as resilience, infrastructure, or economic structures.

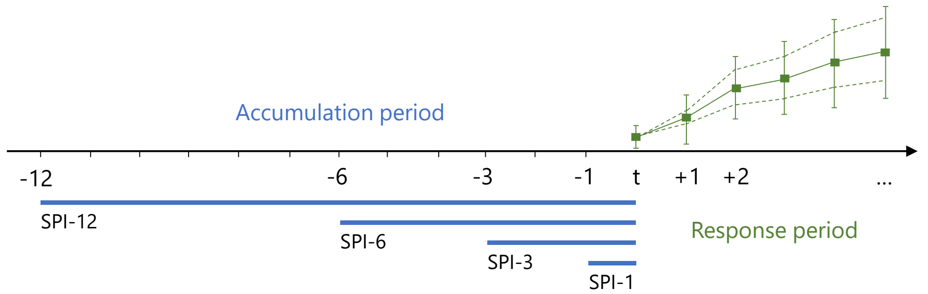


Figure 28
Illustration of response graphs.

This study design estimates how the occurrence of abnormal weather during the various accumulation horizons (SPI-1, -3, -6, -12) leads to responses in formal employment during the response period. Effects are estimated using local projection methods.

After short and wet periods, employment tends to shrink temporarily but recover in subsequent quarters (Figure 29). The opposite is true for short dry periods, with employment decreases up to twelve months later. Interestingly, the response graphs for both wet and dry weather flatten and diminish as accumulation periods become longer (six months or longer). This may be due to anticipatory and adjustments effects, as prolonged weather anomalies give time to the labor force to adapt, or agricultural and related industries adjust their employment needs.

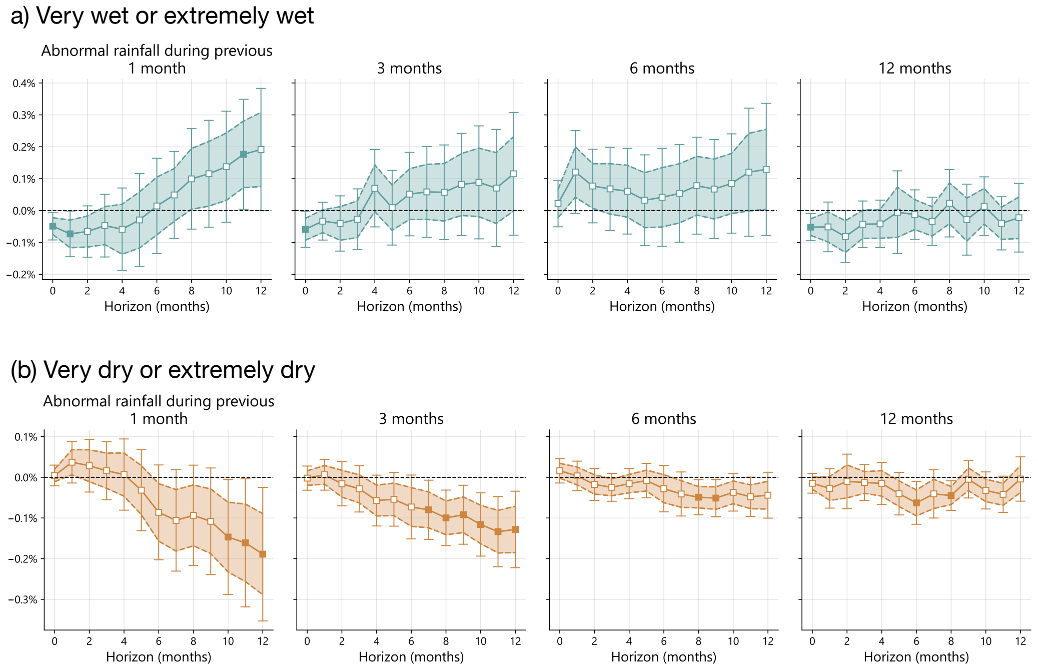


Figure 29
Employment responds to unusual rainfall (all federal units)

The two panels (a) and (b) show the responses of formal employment to rainfall anomalies over various accumulation horizons. After short and wet periods, employment tends to shrink temporarily but recover in subsequent quarters. The opposite is true for short dry periods, with employment decreases up to 12 months later. The responses to wet and dry weather diminish with longer accumulation periods, pointing towards possible anticipation and adjustments effects.

The square markers locate the percentage change over increasing response horizons (horizontal axes). Dark markers indicate effect significance on a 5% level. The dashed lines (whiskers) demarcate the 68% (95%) confidence intervals.

A CLOSER LOOK AT AGRICULTURE

Employment figures in the agricultural sector are likely more dependent on rainfall patterns than are other sectors in the economy. For this reason, we narrow our analysis to the twelve federal units where farming is the most prominent land use and land cover (LULC), as shown in Figure 30.[78] Given their higher share of farming LULC and the sensitivity of agricultural employment to rainfall patterns, we expect more pronounced effects of droughts. Figure 31 presents supporting evidence, by replicating the previous full-country analysis for these units.

The responses in Figure 31a and Figure 31b share similar characteristics. As before in Figure 29, dry and wet weather have opposing effects. The long-term responses are strongest after short-term anomalies. For example, in Figure 31b, after a short-term drought of one to three months, employment figures start to decline, and the effect becomes statistically significant after four months. Interestingly, in Figure 31a, short-term wet seasons lead to increasing employment numbers that become significant after eight months. The growth may be due to harvesting seasons for soybeans, corn, rice and wheat, beginning around four to five months after planting and lasting another four to five months.[79] For both types of anomalies, as the preceding accumulation periods exceeds three months, the response curves diminish. This is likely due to anticipatory and adjustment effects with labor moving to other sectors or regions.

As mentioned earlier, droughts account for more than 92% of Brazil's total losses due to natural disasters. Figure 31c therefore examines the consequences of droughts during harvesting months specifically.[80] Indeed, short-term droughts preceding harvesting seasons lead to immediate drops in employment. The effect size grows with longer response horizons and are highly significant.[81] It is worth mentioning that by narrowing our focus on harvesting months we give more weight to cropland and less to pastureland agriculture.

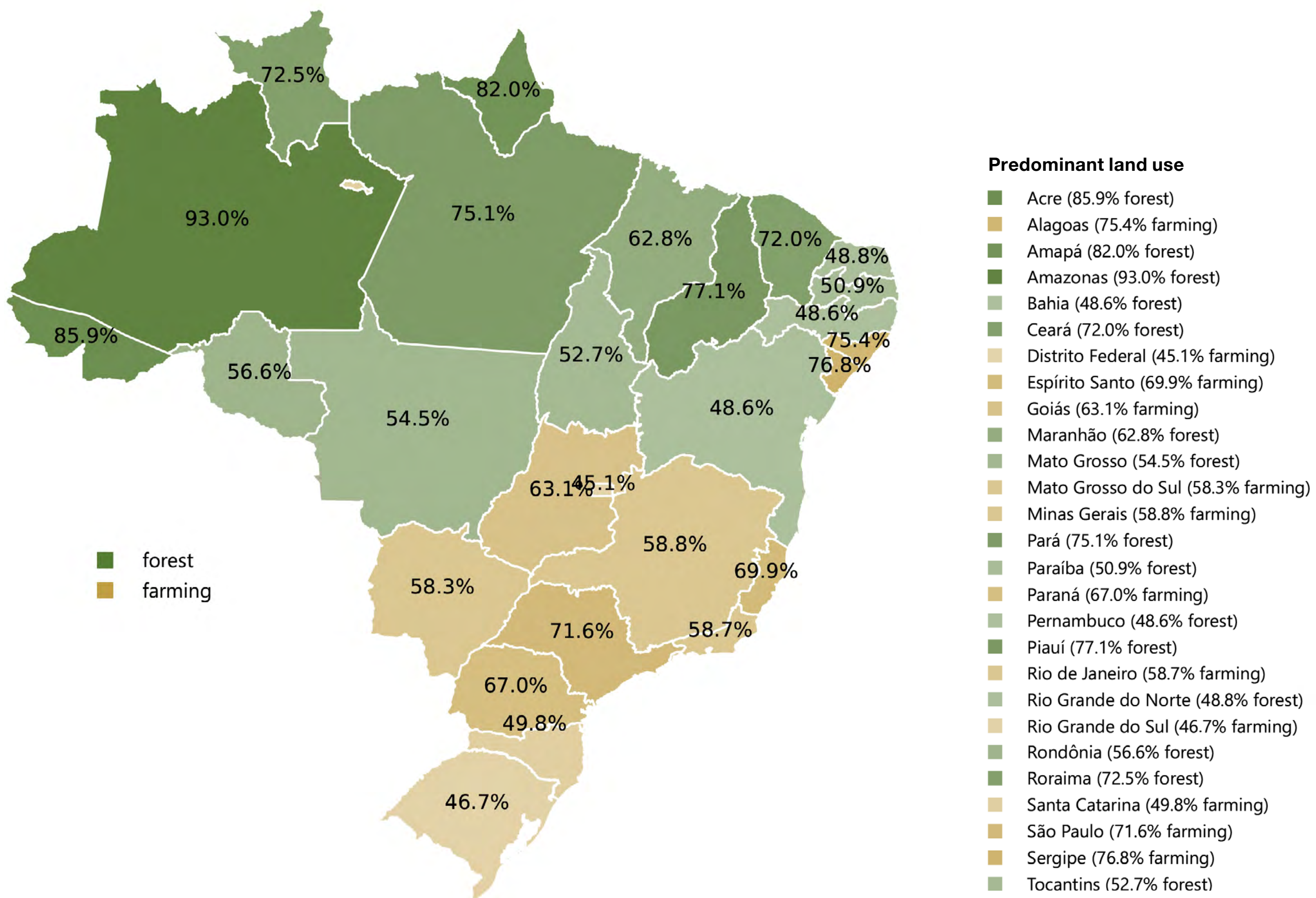
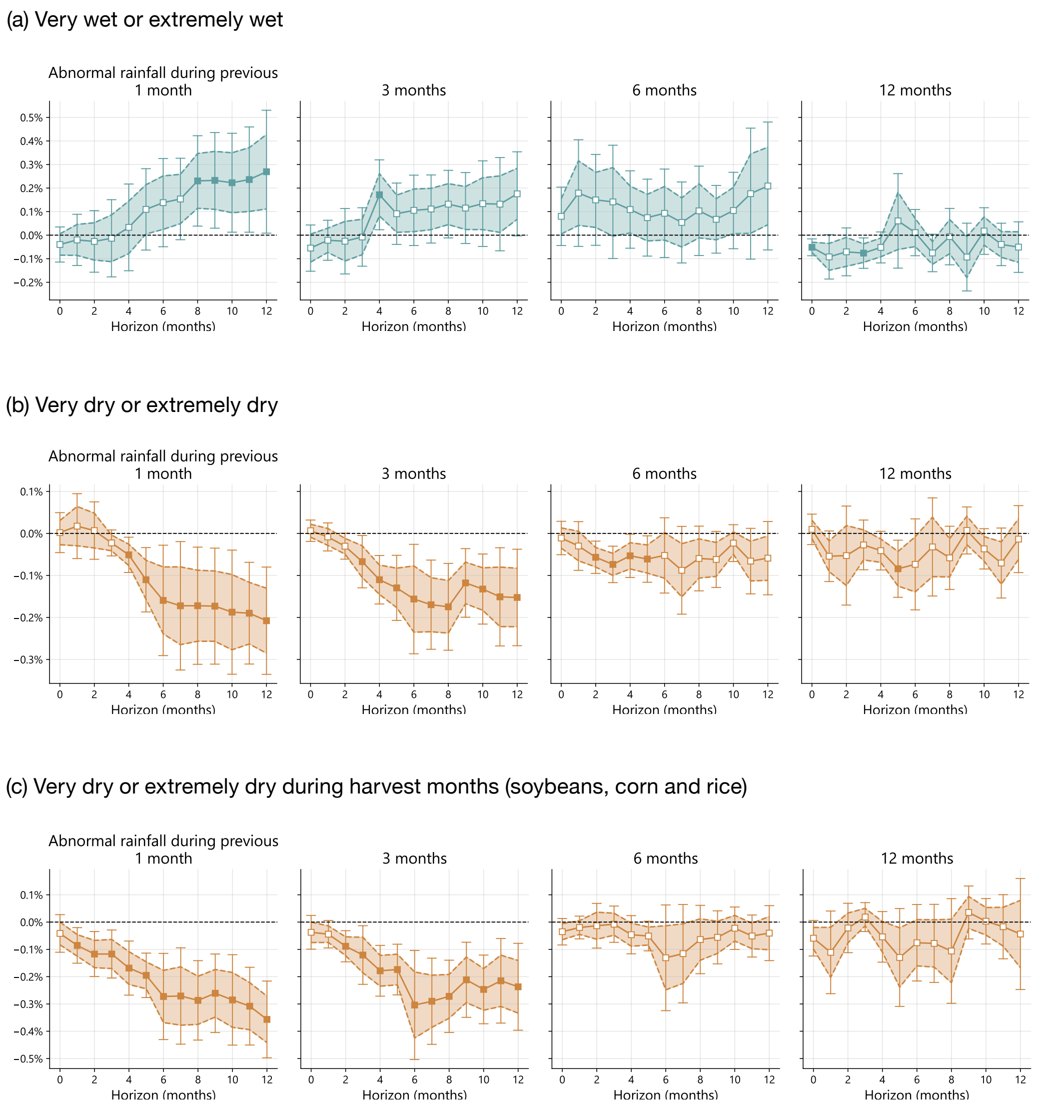


Figure 30 – Predominant land use for each federal unit
The map depicts the most common land use and land cover (LULC) classification for each federal unit in 2020. Forests and farming are the two most common LULCs, compared to non-vegetated areas, water bodies and non-forest formations (Souza et al. (2020)).

Figure 31 – Employment responses to unusual rainfall: predominant farm use LULC units.

The panels (a), (b) and (c) show the responses of formal employment to rainfall anomalies over various accumulation horizons. In panels (a) and (b), unusual rainfall can take place during all months, while in (c), only harvesting months of soybeans, corn and rice are relevant. The responses are in line with findings in Figure 29 but are more pronounced. Shorter droughts (1- to 3-months) have significant effects on subsequent employment during harvesting seasons. As in Figure 29, the effect of longer-term droughts may be alleviated due to anticipatory and adjustment efforts.



DISCUSSION

Sovereign ESG indicators are often available at the country level with an annual frequency. Such a level of aggregation is not always ideal but justifiable, given the large data reporting disparities between countries and the goal of covering as many countries as possible. In comparison, geospatial data is not subject to these limitations and can therefore complement the existing sovereign ESG data landscape. This holds especially true for the environmental pillar, which is plagued by data limitations.[82] Coverage of geospatial data is usually much larger and more consistent but requires additional processing that can be considerable at times. What the researcher gains through the additional resolution – both temporally and spatially – are novel insights into a country that would be otherwise hidden on the aggregated level.

This chapter illustrated how geospatial data could be used to model the effect of rainfall anomalies, especially droughts, on Brazil's federal economies. We found that dry periods are usually followed by lower employment figures in subsequent months. However, this only holds true for shorter dry periods, up to six months. Longer periods have no strong effect as the local economy likely adjusts to the conditions. These findings hold on average for all Brazilian federal units and over all seasons. Given the nature of droughts and the labor market, these effects would have been impossible to identify with annual country data only.

The effects identified are not particularly strong, with a cumulative employment decrease of -0.2% after 12 months. This is likely due to several reasons. First, despite Brazil being an agricultural power house and being among the largest producers for various crops, dairy products and meat, only 9% of the Brazilian work force is employed in agriculture. Second, we only consider formal employment due to data limitations. We therefore almost certainly underestimate the effect, as informal workers play an important role in Brazilian agriculture[83] and are more vulnerable to adverse market conditions. Third, the estimated effect size relates to a single drought only and could accumulate over multiple short-term droughts. Finally, since rainfall anomalies mostly affect agricultural activities, we use land coverage and land use data from satellite imagery to identify the twelve federal units where agriculture constitutes the largest coverage. Results show that indeed, if we only consider short-term droughts during harvesting months in the twelve most farming reliant regions, formal employment drops by -0.4%, which is twice as large as when considering all regions.

OUTLOOK

A key contribution of this report is the flexible modeling approach which allows for quantifying the materiality of biophysical or meteorological events for economic decision makers. As Gratcheva and Wang (2021) argue in their chapter of the recent flagship report "*The Changing Wealth of Nations 2021: Managing Assets for the Future*", a central challenge has been translating an environmentally material quantity (e.g. droughts, forest area coverage, greenhouse gas emissions) into an economically material quantity (e.g. employment figures, inflation numbers, industrial output growth). Only then is it meaningful to discuss their financial materiality that influences the risk management and capital allocation decisions of financial market participants. The approach demonstrated here constitutes one possible way to establish the environmental-economic materiality link. The approach is not limited to precipitation anomalies and employment figures but can be widely applied to study the rapidly growing set of geospatial data sources.

This study could be expanded to integrate other relevant geospatial data such as weather and environmental indicators or land cover transition data, to better identify drought periods and discern which regions and municipalities are most sensitive rainfall anomalies. Furthermore, additional economic indicators would be interesting to explore, such as regional inflation figures or real economic activity, to characterize the effect on the larger economy. A particularly interesting avenue of research would be to investigate spatial spillover effects between regions. For instance, one could estimate whether droughts trigger labor movement towards neighboring states. Alternatively, one could empirically investigate the anecdotal evidence on how droughts in the 1970s lead to migration from the northeast to the southeast of Brazil, thereby contributing to the formation of the favelas. Additional data sources regarding informal labor would be particularly useful, given the large share of informal workers in Brazilian agriculture.

While the findings presented show materiality from an economic perspective, it is much more difficult to ascertain financial materiality regarding Brazil's sovereign bond market. Future work could focus on linking economic materiality to financial materiality – and a corresponding effect on bond market pricing. As the concept of materiality is dynamic, the financial materiality impact could be short-lived or more prolonged and depend on the global economic patterns, such as the commodity cycle. In either case, understanding this link is important for policy makers and financial market participants alike.

In summary, geospatial data is a valuable resource to mend the gaps in sovereign ESG indicators, especially on the environmental pillar. However, better data coverage alone is not enough to improve sovereign ESG. Even though the results of the case study hinged upon the availability of sub-annual and subnational data, the higher resolution alone was not enough to understand how droughts affect Brazil's regional economies. At the same time, the statistical model alone would not have generated any insights if we only had one data point for each year. It was the combination of geospatial data with an appropriate empirical model that enabled us to connect environmental with economic materiality. Establishing these materiality links will be crucial steps towards a better sovereign ESG framework.

KEY PERFORMANCE INDICATORS – WHAT COULD BE GENERATED NOW?

Within this document, we have run through three case studies of what can currently be achieved within the open data space. We have deliberately not attempted to present the results aligned to any standard, or existing initiative. However, of course, the results could be directly applied as metrics, or applied within existing footprint models, to track progress aligned to various common frameworks, such as the SDGs, GRI,[84] IFC Performance Standard 6, or the Natural Capital Protocol.

Much attention is now being given in various forums as to what the various high-level targets are – what agreements nations, companies and financial institutions should adopt around the issue of nature and biodiversity. The question which sits alongside these endeavours and movements is how does one measure performance against these frameworks and commitments? The 'how' arguably is more important than the 'what', as, without clear means of measurement and tracking movement towards the proposed targets will remain unknowable. Data then is the underlying central component that enables application. Where data are not easily available, are inaccurate, or even if there is confusion surrounding what key methods or metrics are, we can expect to see disaffection.

Within the emerging geospatial ESG space, there is now a race to develop the coherent metrics, juggling the differing shortfalls (i.e. cost, accuracy, relevancy, legal rights, temporal consistency) of the data available against the need to develop clear metrics for various standards. The challenge will not be easy and will require improvements not only in the critical asset and observational data, but also in the machine learning and the sophistication of sector-site-specific and user-case-specific products for financial institutions. **To catalyse developments, there ultimately needs to be a collective push from a wide range of stakeholders to guide the rapid development of environmental indicators that are:**

- Low cost, easy to produce
- Accurate and reliable and scientifically robust
- Sensitive to change and allow the separation of impact to a specific asset
- Comparable, across sites and scales
- Applicable across a wide range of sectors, environments, and contexts.

Several large-scale non-profit initiatives are now working to define useful environmental indicators, not necessarily considering application within the financial sector. These initiatives, such as Biodiversity Indicators Partnership (BIP) and IPBES core list of indicators, are now grappling with the issue of identifying robust datasets which can directly or indirectly be applied to create key metrics for national performance to standards such as the CBD and SDGs – a topic mirrored in conversations surrounding the emerging TNFD. BIP, for example, is exploring a number of fully or partially geospatially derived indicators described below. Others such as efforts aligned to the GEO-BON initiative have developed lists of remote sensing indicators for tracking biodiversity [85] (Appendix 1).

In the case studies above, we have touched upon a range of observational datasets which could be used to create generic KPIs, and methods for differing scales. Outlined below is a list of potential metrics which are feasible to generate today. This is not to suggest this is new; such methods or metrics have previously been recommended in a range of standards and are already either directly or indirectly promoted by various commercial tools. However, whilst some indicators can be universal, as the field of geospatial ESG develops, we expect to see more and more sector-specific metrics and models.

POTENTIAL INDICATORS

Here we outline a few examples of proposed high-level KPIs for defining 'environmental' geospatial ESG insights that could be widely applied today. Single metrics ideally should be interlinked, weighted or modelled against other metrics for improved insight. Some must be tailored to the sector;[86] others are more generic.

Overlap of asset with key location attributes, e.g.:

- Biome, Ecoregion, Habitat, Land Cover classifications
- Water Basin
- Elevation
- Assets urban/rural ratio – proximity to urban areas and linear infrastructure

Overlaps of asset with key areas, i.e. PAs, KBAs, WHS, Intact Forest Landscapes, Ramsar Sites, Indigenous lands within the site, and buffers.

- Weighting key areas by secondary variables, e.g.:
  - Designation
  - PA IUCN management category
  - Species data, abundance, diversity, richness, and evenness of species
  - Internet salience of site
  - NGO / Conservation presence
  - Human population presence
    - Temporal valves

- Weighting key areas by 'intactness' indicators, e.g.:
  - Assessment on the intactness of conservation area
    - Assessment of land degradation
    - Site fragmentation
    - The extent of linear infrastructure
    - The extent of commercial activity
  - Assessment of human disturbance of conservation area
    - Temporal valves

Overlap of asset with forest, within the site and the buffer:

- Forest Loss per km^2
  - Temporal values
- Primary Forest Loss per km^2
  - Temporal values
- Secondary Forest per km^2
  - Temporal values
- Forest fragmentation
  - Temporal values
- Intact Forest Landscapes km2
  - Temporal values
- Mangrove forest km^2(Trends)
- Plantation / Managed Forest per km^2
- Palm Oil per km^2
- Dry forest / Cloud Forest km^2

Asset against key biodiversity proxies within the site and the buffer:

- Endangered species range per pixel or within area of interest (AOI)
  - Species data (i.e. total % of species range, abundance, richness, etc.)
- Biome, Ecoregion, Habitat, Land Cover classifications
- Remote sensing products – i.e. Biological effects of irregular inundation, Above-ground biomass, Foliar N/P/K content, Net primary productivity, Gross primary productivity, Fraction of absorbed photosynthetically active radiation, Ecosystem fragmentation, Vegetation height, Specific leaf area, Carbon cycle (above-ground biomass)
- Wider landscape ecoregions, habitats context
  - Connectivity
- Freshwater Biodiversity Exposure
- Indices – i.e. Biodiversity Habitat Index, Species Habitat Index, Wetland Extent Trends Index, Index of Coastal Eutrophication (ICEP) and Floating Plastic debris Density, Reef Fish Thermal Index, Species Protection Index, Wildlife Picture Index in tropical forest protected areas

Asset against key water risk metrics within site and buffer:

- Water Stress, Water Depletion, Interannual Variability, Seasonal Variability, Groundwater Table Decline, Untreated Connected Wastewater, Coastal Eutrophication Potential

Examples of sector-specific monitoring KPIs

- Methane Emissions frequency and density to specific areas, or assets
  - Comparison to reported emission values
- Marine Oil spill detection frequency and density to specific areas, or assets
  - Comparison to reported emission values
- Infra-red heat profile of site as a proxy for carbon dioxide emissions (estimate of the extent of cement factories power usage measured by heat generated)
  - Comparison to reported emission values of an asset
- Ship AIS data
  - Shipping incidents – coral reef groundings, illegal fishing events, marine oil spills etc.

Examples of physical KPIs

Although not directly explored in this paper, where focus instead has been on ‘environmental’ measures, geospatial ESG should be including climate change and physical risk inputs, many of which can be united with other environmental insights to improve overall insight and context

Asset against extreme weather events, within site and buffer:

- Historical Riverine, Coastal or Drought flood risk
- Current dynamic weather data
- Exposure of sector’s critical infrastructure, e.g. length asset of power lines to hurricanes

Asset against key climate change metrics within site and buffer:

- Temperature, precipitation, climate water deficit, wind patterns, reservoir levels, land use patterns for fire suppression, etc across differing scenarios

Of course, many of these potential metrics lack spatial or temporal resolution or fall foul of another limitation to meaningfully or sustainably be applied to drive robust geospatial ESG insights. Significant effort in many cases would need to be applied to convert these datasets to a high frequency high spatial resolution consistent observational portfolio. Luckily, however, with the emergence of new methods and technologies, it may be possible to leapfrog these issues and move to a new generation of environmental observational datasets. We explore these future developments in the next section.

FUTURE DEVELOPMENTS

Geospatial approaches can provide useful insights into the activities of companies and indeed help to differentiate assets, companies and portfolios on initial and ongoing environmental impact. With growing interest in the application, there are now actors working on building data exchanges and newer tools to support asset and supply chain data improvements for application within this space.[87] Beyond the issues with asset and supply chain data, as discussed throughout this paper, there is still much work to be done to produce an effective, consistent environmental observational data stream to enable and support robust geospatial ESG environmental insights, where it is vital to:

1. improve the temporal and spatial resolution of environmentally relevant geospatial datasets for application in geospatial ESG to aid the generation of up-to-date insights;
2. use improvements in technology and methods employed to break through critical bottlenecks to ensure relevancy and coverage of critical topics;
3. improve commercial access to ‘environmental’ relevant data held by the IGOs, NGOs and academic institutions – either via open data standards or effective commercial licensing and distribution solutions.

Fortunately, various actors are already working to resolve these issues. In this section, we highlight some of the work being undertaken to provide solutions to the challenges faced.

BOX FIVE

IMPACT OBSERVATORY – OBSERVATIONAL DATA IMPROVEMENTS – UPCYCLING WITH AI

Authors: Steven Brumby, CEO/CTO & Co-Founder – Impact Observatory
and John Barabino, Co-Founder & Head of Business – Impact Observatory

There has been an explosion of research in the AI field of deep learning, resulting in open-source algorithms and automation software for rapid, large-scale image analysis. Adaptation of these techniques to satellite and aerial imagery has led to the creation of a number of space data analysis companies, including Orbital Insight, Descartes Labs, SpaceKnow and Impact Observatory, as well as major programmes to add machine learning capabilities within existing geospatial technology companies, e.g., Esri ArcGIS, Maxar GBDX, Planet PlanetScope, Airbus UP42, Google Earth Engine and Microsoft Planetary Computer. Open-source code repositories and coding communities enable sharing and reuse of geospatial algorithms and are democratizing access to knowledge previously available to only a few government agencies and technology companies.

Applying on-demand geospatial data to foundational ESG challenges

ESG applications supporting both private and public good organizations commonly require an understanding of land use and land cover (LULC) change processes across many years, and across seasons within a given year. Understanding patterns in LULC change can provide insights about resource exploitation, biodiversity habitat reduction, loss of ecosystem services and fluxes in natural storage of carbon. Impact Observatory has developed deep-learning algorithms that use 10m Sentinel-2 imagery to create dynamic, global LULC time series datasets to inform decision making and monitor impact.[88] This global 10m LULC time series product provides over 100 times the spatial resolution of previous global open science products such as the Copernicus CGLS-LC100 100m resolution dataset or the NASA MODIS 500m dataset. Automation enables timely updating of the LULC map within the year and near-real-time monitoring, compared to traditional map products that are only updated after one to several years delay. Similar global 10m LULC products are planned by other teams, e.g. the ESA WorldCover programme, and teams leveraging Google Earth Engine and Microsoft Planetary Computer.

From land cover time series to dynamic science products

Building on this LULC monitoring capability, Impact Observatory partners with leading academic and environmental NGO science teams with expertise in specific ecosystem services, such as carbon storage, biodiversity intactness and measuring the 'footprint' of human development. Impact Observatory automates and scales these published science models to create automated global datasets as openly licensed science products.

The human footprint dataset combines land use information with population pressure, built infrastructure and accessibility data to map and assess human pressures across the globe at 1km resolution. These maps are critical for identifying remaining wilderness areas to aid in planning and management efforts. Impact Observatory worked with the human footprint academic team to reprocess the human footprint globally for 2017–2020 at 100m resolution. The results show high agreement with previous human footprint maps, with the ability to now run these on demand.

As with human footprint, Impact Observatory has also partnered with the UNEP World Conservation Monitoring Centre (WCMC) to operationalize the calculation of the biodiversity intactness index (BII) and above-ground biomass carbon change. The models used to create these science products use LULC time series, which can now be automated and run on demand. Impact Observatory has partnered with WCMC to create global 100m products that can be generated on demand and released annually as a public good.

Impact Observatory's industry partners fund the development and processing of this work, which provides industry, finance and governments with near-real-time, on-demand, science-based insights, and allows Impact Observatory to release public good, global LULC and derived science time series products on an annual basis.

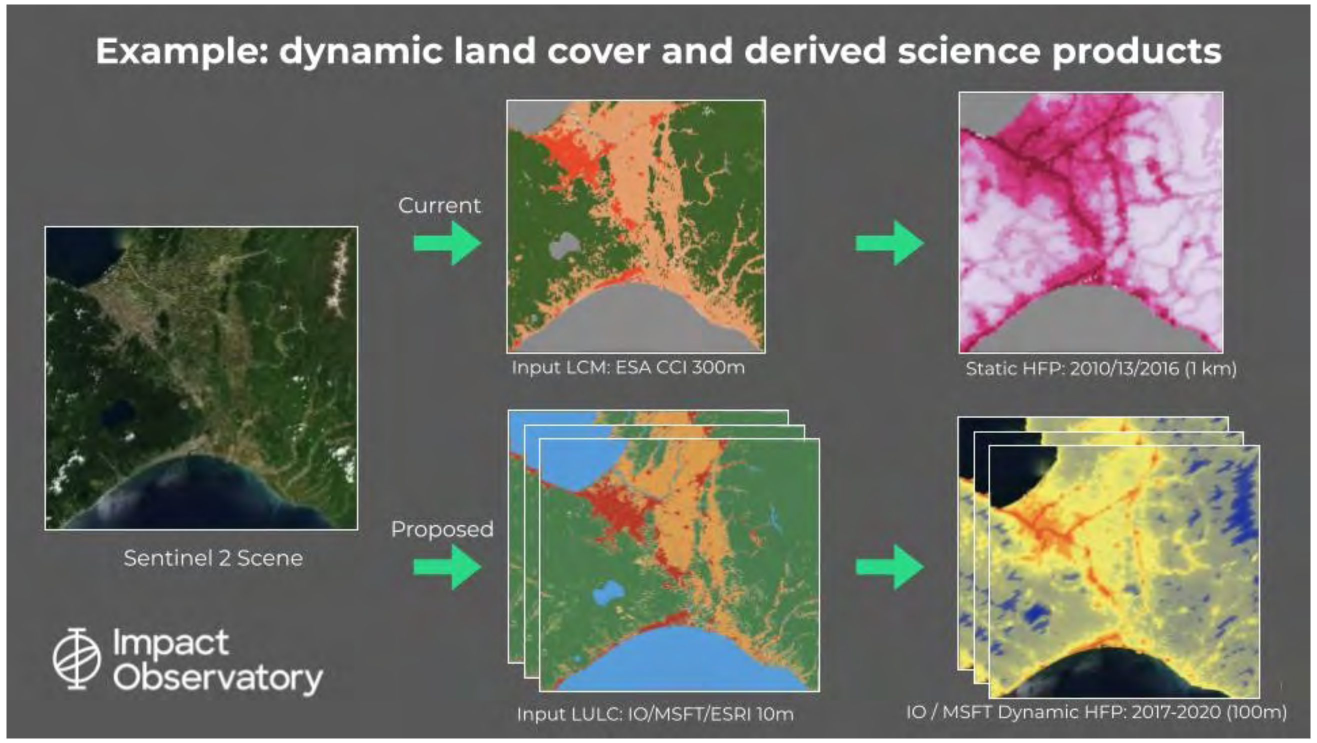


Figure 32 – Impact Observatory near-real-time, on-demand land use land cover (LULC) provides global 10m maps for planning, reporting and monitoring. These maps enable creation of dynamic science products that increase the spatial resolution and timeliness of important measures for climate, biodiversity and sustainable development.

Data improvements on biodiversity

One of the most important observational variables to get right from an environmental perspective is accurately defining impact on biodiversity. Measuring biodiversity and then impact is extremely challenging. Traditional field sampling, whilst excellent, is slow and resource intensive and as a result impractical as a method to create accurate high frequency global insights. The alternative solution commonly promoted is the reshuffling of the current global species datasets into new data products, using various new statistical approaches or some other means. Such approaches are arguably unlikely to break significant ground, as all these 'new' products rest upon the same limited data. Instead, if we are to radically improve insight on the extent and trends in species globally, entirely new data collection approaches will be required.

Substantial global aggregates of species data already exist, such as GBIF,[89] which provide vital data. However, these initiatives need to be supported by more regular and higher frequency field data if they are to provide strong geospatial ESG insights able to show subtle changes and trends in degradation to habitats over short time frames. Indeed, recognising the need for more data, under the Data4Nature initiative,[90] corporates are encouraged to upload their species records created during impact assessments into GBIF.

Fortunately, novel ground sampling methods are emerging that are capable of offering greater and greater insight into what species are actually present and potential insights into trends and degradation of ecosystems in much more real-time. For example, developments on bioacoustics – recording the ratio of natural vs. non-natural noise within a landscape and the structure and gaps within a soundscape – combined with machine learning offers interesting potential of being able to better understand the high level health of a landscape with much lower sampling requirements. Initiatives such as Wildlife Insights[91] and the eBioAtlas Freshwater eDNA initiative[92] offer a vision of the future where multiple forms of sampling data (e,g, eDNA, camera trap, audio) are combined together to help refine remote sensing products. Here we look at one of these technologies: eDNA.

BOX SIX

NATUREMETRICS – IMPROVEMENTS WITH DNA-BASED APPROACHES

Author: Dr Cath Tayleur, Head of Nature Positive Supply Chains – NatureMetrics

Challenges with traditional field sampling approaches

Traditional sampling suffers from its inability to scale, both over space and time, but also over species, as an astonishing 86% of land species and 91% of ocean species remain undiscovered.[93] As we move beyond biodiversity being included in decisions simply for its intrinsic value, to its importance in underpinning economies and global health, we need ways to encapsulate the full complexity of life on earth. Biodiversity monitoring needs to capture those species, communities and their characteristics that are the real engine driving ecosystems. For example, without the multitude of bacteria and fungi that make up the soil microbiome, global agriculture would grind to a halt, yet our knowledge of life below earth is only starting to capture the complexity of this system.[94] One of the key barriers has been the need to have trained experts in the field able to identify target species by sight, sign or sound. New approaches to biodiversity monitoring are required that democratize data collection, allowing a wider range of stakeholders to participate using standardized, simple and effective protocols.

How DNA-based monitoring can overcome these challenges

DNA-based approaches include environmental DNA (eDNA), the traces that species leave behind in the environment, and in other cases the sampling of the organisms themselves, such as with bulk samples of insects. A bit like crime scene forensics, the individual fingerprints detected through samples of soil, sediment, water and even air are then matched to reference libraries that contain the sequences of thousands of species (Figure 33), giving us a snapshot of whole biological communities.

This process of DNA metabarcoding generates data at a scale that has never previously been feasible, allowing a more comprehensive overview of biodiversity, including the small and diverse organisms (e.g., insects, soil fauna, plankton, fungi, bacteria) that are often closely linked to the ecological functions of particular habitats[95] and ecosystem services.[96]

Environmental DNA (eDNA) sampling

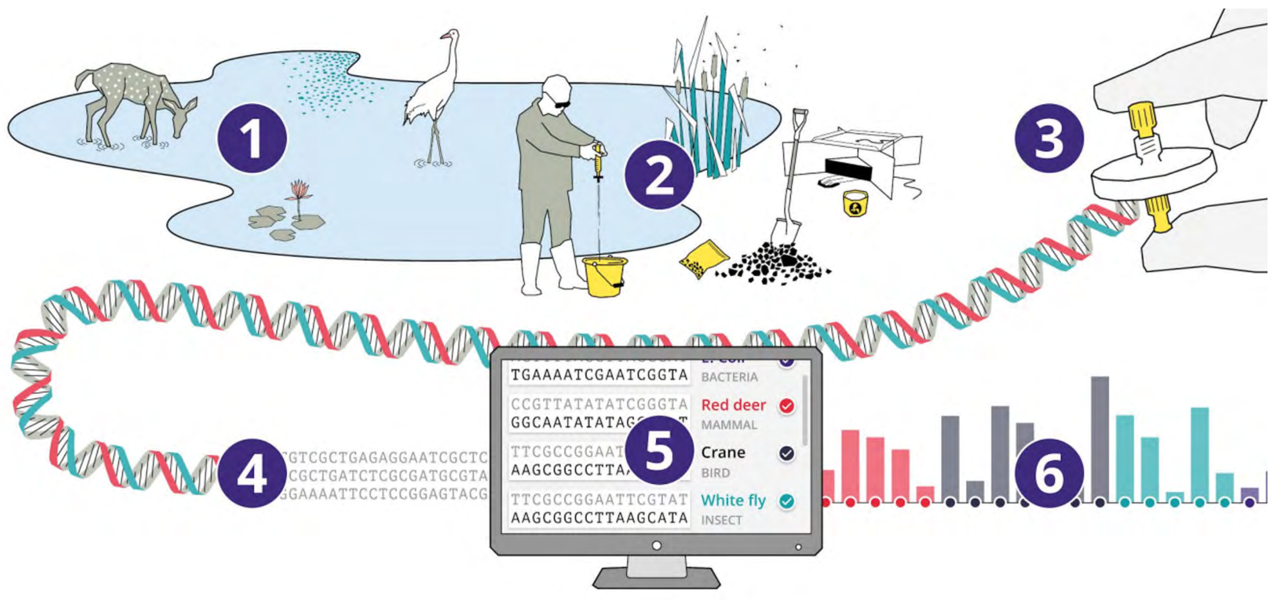


Figure 33 – The process by which eDNA enters the environment, is collected, processed, sequenced and turned into biodiversity data.

A substantial body of research literature now demonstrates that DNA-based methods can match or outperform conventional survey methods for many species and groups, and often bring advantages in terms of cost and survey effort, increased detection sensitivity and increased taxonomic resolution.[97] For example, NatureMetrics has shown that in the field you can survey more species in just 10% of the field time when compared to traditional approaches. Compared to other high-tech biodiversity solutions, eDNA has the benefit of a relatively low-tech approach to field data collection, making it accessible to everyone including local communities and other stakeholders.

DNA-based monitoring offers the ability to make surveys easier to conduct and replicate. Species identification is automated in the lab, removing the subjectivity of field-based species detection. DNA samples can also be stored for future analysis; such repositories could be used in future to conduct independent audits of biodiversity claims.

Figure 34 – Using a filter to capture the DNA of a wide range of species that are present in and around water.

Future directions for the DNA-based biodiversity data revolution

The scalability of DNA-based monitoring means that we can gather more data on more species, and ultimately make more informed, evidence-based decisions around biodiversity. This has implications for a wide range of applications – from systematic conservation planning and evaluation of conservation outcomes to due diligence and environmental impact assessment. KPIs linked to species and/or ecosystem health could inform the sustainability linked products of the future.

There is a huge opportunity to apply 'big data' approaches to DNA-based datasets in order to better understand how ecosystems function and respond to change. With large-scale monitoring, such as eBioAtlas, we can build algorithms to identify the signatures of healthy and resilient ecosystems and use these to inform KPIs. DNA-based approaches can be used to help validate the link between pressures and outcomes, ground-truthing the predictions of model-based assessments. We can set and measure progress towards meaningful restoration and 'net positive' targets, maintaining and improving the underlying functions of ecosystems. Finally, we can link field data to powerful earth observation data, allowing us to better see biodiversity from space, achieving even greater scale and allowing us to track changes in near-real-time.

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FINAL REFLECTIONS

The world of geospatial ESG is at an exciting point in time, with its potential only just beginning to be recognized and explored in the mainstream. This growth and novelty is reflected in many of the open and commercial geospatial ESG platforms currently emerging, where arguably many underutilize the full range of technical approaches available. In the diagram on the following page (Figure 35), we've simplistically classified the various key components of a geospatial ESG platform. If you look at any given tool, many are only getting started using the basic elements, such as a direct comparison to asset locations using multiple layers. Although of course there are exceptions – tools which use far more sophisticated sector and site weightings, observation data refinement and various forms of machine learning.

Throughout this document we have shown the simplest approaches and introduced some of the more complex elements. It is exciting to consider that many actors are now moving beyond this to develop more robust solutions in this space. Combined with improvements in remote sensing and ground data collection, we expect in the near term improved geospatial ESG outputs with far greater accuracy and insight into the 'environmental performance' of assets, commercial actors and even national states.

While there is much to expect from the emerging field, there are external limitations which may undermine progress such as access to asset and supply chain data. From the environmental data perspective, perhaps the key challenge is around the diversity of data sources. Where data providers will need to integrate, often continuously, a huge range of differing data sources held by a diverse range of NGOs, intergovernmental agencies, academia, the private sector and commercial data providers. Since no single actor will be capable of providing all these data sources, a shift will be required in how data is aggregated, suggesting that new approaches to data sharing will be required. It seems probable that this might be achieved via secure interconnected data marketplaces, perhaps using a tested and well-developed open standard to aid adoption; however, the design and terms of such an exchange is beyond the remit of this paper.

Figure 35 – Diagram illustrating various key components available to geospatial ESG platforms, many of which are expected to come into mainstream development shortly.

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APPENDIX

Appendix 1 – Remote sensing product suggestions as priority biodiversity metrics (from Skidmore et al. 2021):

- Biological effects of fire disturbance (direction, duration, abruptness, magnitude, extent and frequency)
- Biological effects of irregular inundation
- Leaf Area Index
- Land cover (vegetation type)
- Ice cover habitat
- Above-ground biomass
- Foliar N/P/K content
- Net primary productivity
- Gross primary productivity
- Fraction of absorbed photosynthetically active radiation
- Ecosystem fragmentation
- Ecosystem structural variance
- Urban habitat
- Vegetation height
- Plant area index profile (canopy cover)
- Habitat structure
- Fraction of vegetation cover
- Specific leaf area
- Chlorophyll content and flux
- Land surface peak (maximum of season)
- Land surface green-up (start of season)
- Land surface senescence (end of season)
- Carbon cycle (above-ground biomass)
- Peak season (maximum of season)
- Green-up (start of season)
- Senescence (end of season)
- Leaf dry matter content
- Ecosystem soil moisture
- Functional diversity
- Species abundance
- Relative species abundance
- Population density

ENDNOTES

1. Some commercial outfits, such as Verisk Maplecroft, have for over a decade focused on integrating geospatial data into ESG. Arguably now interest has become more mainstream, from financial institutions, within major policy, and within IGOs and NGOs. For example, new publications are emerging on the subject from financial institutions, such as Swiss Re (2021).
2. To avoid confusion, here we use the term 'geospatial ESG', defined as 'the use of geospatial data to generate ESG relevant insights into a specific commercial asset, company, portfolio or geographic area', rather than other terms such as 'spatial economics' or 'spatial finance', which are commonly used to refer to any application of geospatial data within finance, e.g. remote sensing derived crop yields for commodity trading insights.
3. Within this document, due to our expertise, focus is placed on the 'E' pillar in ESG
4. Such as Orbital EOS
5. Such as EarthKnowledge
6. Such as GHGSAT, MethaneSAT
7. Such as Kayrros
8. Such as Global Forest Watch Pro and Trase
9. Taskforce on Climate related Financial Disclosure
10. Taskforce on Nature-related Financial Disclosures
11. Demonstrated by growing attention to the topic in wider forums and bodies such as the World Economic Forum
12. Stephenson and Carbone (2021)
13. UNEP-WCMC (2017)
14. Stephenson and Carbone (2021)
15. World Bank; WWF (2020)
16. It's important to note that sovereign level insights would not exclusively draw from asset level results, but would derive their own sub-national and national environmental metrics from the same observational datasets used with asset level assessment, and potentially, summed relevant asset level insights.
17. See here for more information on STAR
18. For example, NASA Global Ecosystem Dynamics Investigation Lidar and the German Aerospace Centre's high-resolution and wide-spectrum satellite programme EnMAP
19. Hilton and Lee (2021)
20. Within this document we focus on defining 'environmental' impact related to biodiversity. We do not attempt to discuss these impacts in terms of material, reputational, regulatory or physical risks. Whilst geospatial approaches can provide robust insights into physical risks such as coastal flooding risk, extreme weather risk, real-time weather risk, etc., we do not include them directly as an area of focus within this document.
21. It should be apparent that looking at values in isolation from one another is not a robust approach: ecosystems are heavily connected, and subsequently observed values will cascade and impact upon another. However, for a rapid high-level screening, the approaches outlined here should suffice and provide a useful starting point in the concept, and they can of course be further refined.
22. Within this paper, for simplicity, we do not integrate, or discuss climate change data. However, climate change is heavily intertwined with biodiversity loss and should be considered alongside environmental metrics.
23. Here we assume the current data reality where ground data from power plants themselves, or any asset, isn't available. As such we have to apply other data approaches to independently gain as much insight as possible. Of course, if highly granular site level data on their operations were obtainable, these methods would be unnecessary.
24. The term 'open' is used as a generality here; the data layers reviewed have differing licensing constraints, ranging from fully open for any application, open for non-commercial use, to restricted, requiring written permission for use. However, these datasets and their licensing variability could be considered indicative of the 'public' or 'open' environmental geospatial space.
25. The term 'open' is used as a generality here; the data layers reviewed have differing licensing constraints, ranging from fully open for any application, open for non-commercial use, to restricted, requiring written permission for use. However, these datasets and their licensing variability could be considered indicative of the 'public' or 'open' environmental geospatial space.
26. 76% (105) of the 137 data layers publicly listed, data layers which were unsuitable were excluded e.g., 'demo layers' – data reviewed as at 11/03/2021
27. Jarić, Quétier and Meinard (2020)
28. Tian et al. (2020)
29. Battistella et al. (2018)
30. O'Connor et al. (2015)
31. Skidmore, et al. (2015)

32. Biodiversity can be defined loosely as the variety of life found within an area. Throughout this document, we deliberately do not strictly define the term, reflecting the reality that within the ESG space, there are a wide range of geospatial data products that present, or could potentially provide, insights relevant to biodiversity and as such are often communicated around or within the 'biodiversity' label. A wide range of indirect proxies such as 'freshwater' or 'legal area delineations' are used, which without actually being a direct measure of biodiversity, may still arguably provide some useful insight within ESG applications.

    However, for reference, IPBES provides an accurate definition: 'Biodiversity is the variability among living organisms from all sources, including terrestrial, marine and other aquatic ecosystems, and the ecological complexes of which they are a part. This includes variation in genetic, phenotypic, phylogenetic and functional attributes, as well as changes in abundance and distribution over time and space within and among species, biological communities and ecosystems.' (Intergovernmental Panel on Biodiversity Ecosystem Service, 2019).
33. Here we define 'near-real-time' as updates every month within a month, i.e. January's results before the end of February.
34. The term 'open' is used as a generality here, the data layers reviewed have differing licensing constraints, ranging from fully open for any application, open for non-commercial use, to restricted, requiring written permission for use. However, these datasets and their licensing variability could be considered indicative of the 'public' or 'open' environmental geospatial space.
35. See Appendix 1.
36. Skidmore, Coops et al. (2021)
37. Vihervaara et al. (2017)
38. Such as Ecometrica
39. Such as Earth Knowledge
40. IPBES (2019b)
41. IPBES (2019a)
42. WWF (2020)
43. World Economic Forum (2020)
44. Salafsky et al. (2008)
45. These types of assessments are viable and scalable. To guide its work and insight, the WWF Conservation Intelligence team has since 2016 run global scale assessments on millions of mining, oil and gas, power, infrastructure and other assets against 50+ observational datasets every quarter.
46. All the mines reported here are to illustrate the geospatial approach and the complications which may arise. They serve as examples only; the authors are making no delineation or statement as to the environmental or ESG performance of these assets.
47. Here we use a simple, generalised area value of 1km² for each mine to illustrate the method and results in its simplest terms. Using a slightly more sophisticated approach, it is possible to consider assets exactly by their concession areas or exact measured footprint, and/or by an estimated footprint. For example, Theobald et al. 2020, using a sampling approach, estimated mines' footprints into four type of mines by commodity: 1) coal; 2) hard-rock (bauxite, cobalt, copper, gold, iron ore, lead, manganese, molybdenum, nickel, phosphate, platinum, silver, tin, U3 O8, and zinc); 3) diamonds; and 4) other (antimony, chromite, graphite, ilmenite, lanthanides, lithium, niobium, palladium, tantalum, and tungsten). They used an estimated mean area of 1) 12.95km2 for coal; 2) 8.54km2 for hard-rock; 3) 5.21km2 for diamonds; and 4) 3.40km2 for others. https://essd.copernicus.org/preprints/essd-2019-252/essd-2019-252.pdf
48. The IUCN Red List, World Database on Protected Areas and Key Biodiversity Areas global datasets are available for commercial application via the IBAT Platform.
49. Olson et al. (2001)
50. Newbold et al. (2016)
51. Ruesch & Gibbs (2008)
52. Hansen et al. (2013)
53. Hansen (2020): SCI (2020 version)
54. Hansen (2020): FSII (2020 version)
55. Protected Areas (PAs) often exist in the same spatial area with multiple designations covering one area. For example, a National Park boundary may also be designed as a World Heritage Site.
56. Here we use a simple generalised area value of 1 Km² for each mine to illustrate the method and results in its simplest terms. Using a slightly more sophisticated approach it is possible to consider assets exactly by their concession areas or footprint, and or by an estimated footprint. See Theobald et al. 2020.
57. Values may exceed 100% overlap, as multiple protected area designations may occupy the same spatial extent. More complex measurements are easily achievable, such as depth of assets within the conservation area, fragmentation, etc.
58. Results reported here do not in any way report an actual factual position of WWF, or any other of the institutions or authors, on the environmental impact or ESG performance of these mines or companies, nor their rankings. Results are not consistent; they show examples of mines with medium to high scores, excluding records to randomise results.
59. IUCN Category V – A protected area where the interaction of people and nature over time has produced an area of distinct character with significant ecological, biological, cultural and scenic value, and where safeguarding the integrity of this interaction is vital to protecting and sustaining the area and its associated nature conservation and other values (IUCN, 2013). https://portals.iucn.org/library/node/30018
60. IUCN Category VI – Protected areas conserve ecosystems and habitats together with associated cultural values and traditional natural resource management systems. They are generally large, with most of the area in a natural condition, where a proportion is under sustainable natural resource management and where low-level non-industrial use of natural resources compatible with nature conservation is seen as one of the main aims of the area (IUCN, 2013). https://portals.iucn.org/library/node/30018
61. For example, see the Digital Observatory for Protected Areas
62. Provided as an example; more complex assessments are possible, for example it is possible to consider the range of a species and the dependence of that species to a specific site – e.g. does it constitute 100% of its range or 1%, and against other ecological values such as known habitat types and elevation.
63. Beyond geospatial approaches, some actors may have gained insight into supply chain footprints using Environmentally Extended Input-Output models and other methods.
64. Facciolo, De Franchis & Meinhardt-Llopis (2017)
65. ESG investing refers to an investment process where ESG factors are either used as inputs into financial decision-making (e.g. to identify risk factors or guide investment allocations) or to measure the outputs of the investment (e.g. emission reductions or sustainable forest management). We refer the reader to (Gratcheva et al. (2021)), who discuss the underlying dual materiality concept.
66. Overall institutional assets are estimated at about US$100 trillion. Current estimates of ESG-themed strategies amount to about US$ 40 trillion (Gratcheva et al. (2021)).
67. A benchmark index describes the performance of a group of financial securities, such as stocks or bonds. The benchmark's constituents are weighted to best reflect the group's overall performance. In the stock market, the S&P500 tracks the 500 largest US listed companies, which are weighted based on their market capitalization. ESG integration into an index would adjust the constituents' weights to also reflect their ESG practices.
68. lanalp et al. (2020))
69. (Gratcheva, Emery, and Wang (2021)), (Gratcheva et al. (2021))
70. In addition, ESG providers tend to construct Social and Governance indicators based on similar sources.
71. (Dang et al. (2021))
72. For further discussion about the difference between environmental and economic materiality, we refer to (Gratcheva and Wang (2021)).
73. (World Meteorological Organization (2012))
74. For example, the Palmer Drought Severity Index (PDSI), Integrated Drought Index (IDI), the Next Generation Drought Risk Index (NGDI), the Weighted Anomaly Standardized Precipitation (WASP).
75. Climate Risk Profile: Brazil (2021): The World Bank Group
76. (United Nations Office for Disaster Risk Reduction (2021))
77. Impulse response graphs are commonly used in economics to assess the effect of a sudden change ("shock") in an input variable (e.g. interest rate changes) onto an output variable of interest (e.g. employment) over an extended time horizon.
78. While the LULC changes over time, units and their most prominent LULC are constant throughout the sample. For farming, which includes pastureland and cropland (annual, perennial and semi-perennial) as well as combinations thereof (Souza et al. (2020)), we identify the following twelve units (descending order): Sergipe, Alagoas, São Paulo, Espírito Santo, Paraná, Goiás, Minas Gerais, Rio de Janeiro, Mato Grosso do Sul, Santa Catarina, Rio Grande do Sul, Distrito Federal.
79. (AMIS (2012))
80. Harvesting seasons for soybeans, corn (first crop) and rice begin in January and end in May and June (AMIS (2012)).
81. We employ the future bias correction from (Teulings and Zubanov (2014)). Without it, we would assume that no droughts happen during the response period, which is unlikely.
82. (Gratcheva, Emery, and Wang (2021))
83. (Henley, Arabsheibani, and Carneiro (2009))
84. Global Reporting Initiative (GRI) (2016)
85. Skidmore et al. (2021)
86. A tension arises here: the more sector specific the metric, potentially the more informative; however, also potentially the harder it will be to scale the metric and to integrate it with other more generic metrics at the portfolio level.
87. Such as the Green Digital Finance Alliance (GDFA) – Open-Source Biodiversity Data Platform Initiative
88. Karra et al IGARRS 2021
89. GBIF
90. Data4Nature initiative
91. Wildlife Insights
92. eBioAtlas
93. Mora et al. (2011)
94. Fierer (2017)
95. Seymour et al. (2021)
96. Schadewell & Adams (2021)
97. Fernández et al. (2021)