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THE BIODIVERSITY DATA PUZZLE

EXPLORING GEOSPATIAL APPROACHES TO GAIN IMPROVED 'BIODIVERSITY' INSIGHT FOR FINANCIAL SECTOR APPLICATIONS AND THE PRESSING NEED TO CATALYZE EFFORTS

COVER IMAGE: Maxar GeoEye-1 satellite image showing flamingos, Lake Nakuru National Park, Kenya, on June 14, 2010. Satellite image © 2022 Maxar Technologies.

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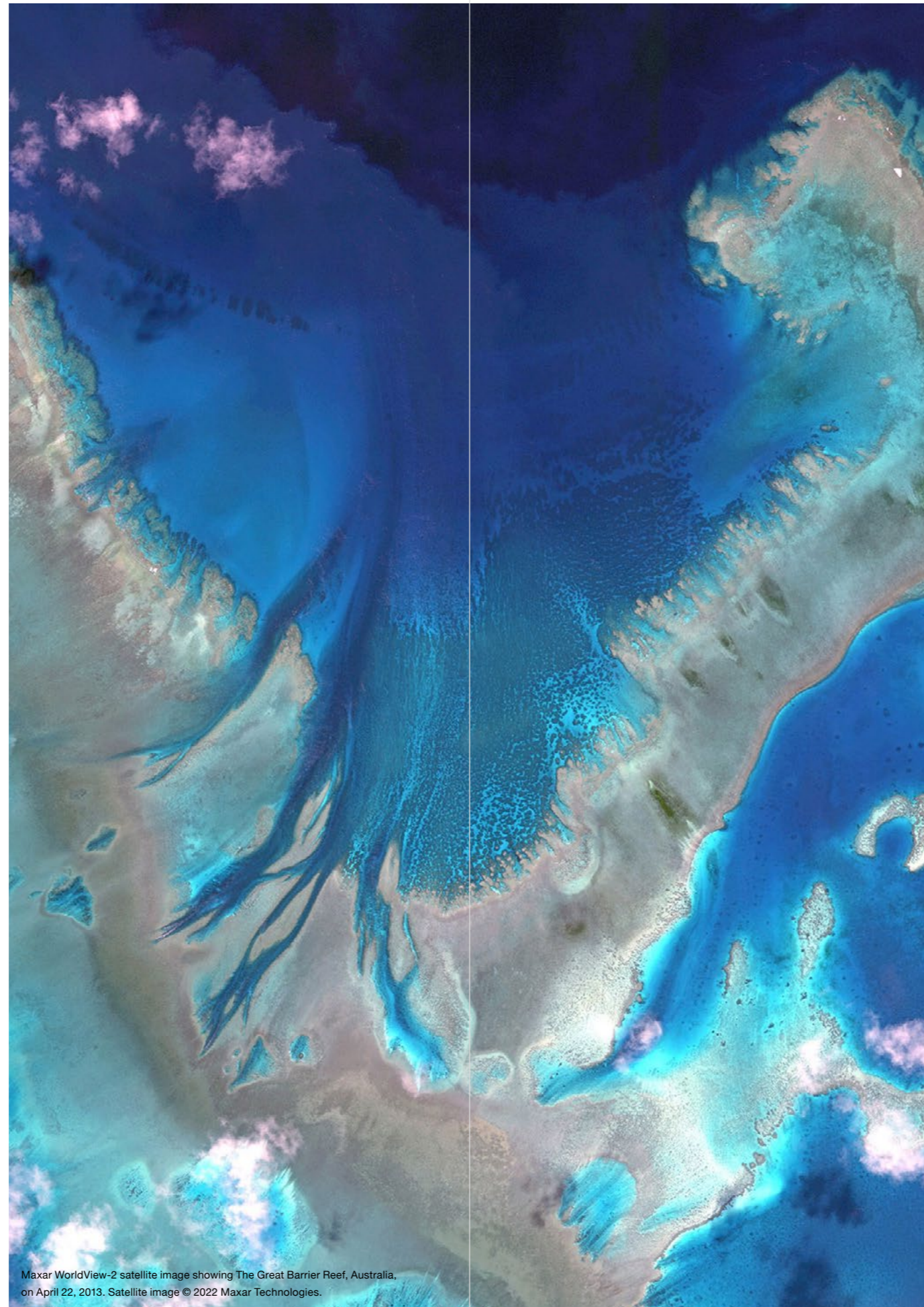
WWF is an independent conservation organization, with over 30 million followers and a global network active in nearly 100 countries. Our mission is to stop the degradation of the planet’s natural environment and to build a future in which people live in harmony with nature, by conserving the world’s biological diversity, ensuring that the use of renewable natural resources is sustainable and promoting the reduction of pollution and wasteful consumption.

Find out more at wwf.org.uk

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Maxar Technologies (NYSE:MAXR) (TSX:MAXR) is a provider of comprehensive space solutions and secure, precise, geospatial intelligence. We deliver disruptive value to government and commercial customers to help them monitor, understand and navigate our changing planet; deliver global broadband communications; and explore and advance the use of space. Our unique approach combines decades of deep mission understanding and a proven commercial and defense foundation to deploy solutions and deliver insights with unrivaled speed, scale and cost effectiveness. Maxar’s 4,400 team members in over 20 global locations are inspired to harness the potential of space to help our customers create a better world. Maxar trades on the New York Stock Exchange and Toronto Stock Exchange as MAXR.

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Maxar WorldView-2 satellite image showing The Great Barrier Reef, Australia, on April 22, 2013. Satellite image © 2022 Maxar Technologies.

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GLOSSARY¹

Asset	A physical entity owned by a parent company either directly, partially or via its subsidiaries. These assets can be non-static, moveable (e.g. an oil rig, or aircraft). Assets do not include the production assets of a company (e.g. the production cars of a car manufacturer) but only those assets used within the company's operations to enable production.
Asset Data (Asset Dataset/s)	Geospatially definable data which at a minimum defines the location (X, Y) coordinates and ownership of a given set of assets. Frequently, asset datasets are sector specific and contain additional attributes tracking variables relevant to the specific asset class. More robust asset datasets track more attributes and use polygons to accurately geolocate assets and property extent. Note: Asset datasets are both openly and commercially available, with six or seven sectors currently well documented in commercial offerings. No widely adopted standard exists for these datasets.
Baseline	An estimate of the prior status of ecosystem condition or biodiversity for a given time and area.
Biodiversity	Biodiversity is the variability among living organisms within species, between species and between ecosystems. Biodiversity underpins the proper functioning of ecosystems. A more complete definition of biodiversity is from the United Nations Convention on Biodiversity (CBD): 'The variability among living organisms from all sources, including, inter alia, terrestrial, marine and other aquatic ecosystems and the ecological complexes of which they are part; this includes diversity within species, between species and of ecosystems' (CBD, 1992).
Company (Company-Level, Parent Company)	Refers to the legal entity which owns or controls the majority interest of other entities, such as subsidiaries and assets.
Cumulative Impact/s	Impact/s, both direct and indirect, that interact, aggregating to cause further impact to ecosystem condition. TNFD, 2022 use the following definition: 'A change in the state of nature (direct or indirect) that occurs due to the interaction of activities of different actors operating in a landscape'
Direct Impact/s (Destructive Impact/s)	Impact/s that permanently (5 years+) destroy habitat. TNFD, 2022 uses the following definition: 'a change in the state of nature caused by a business activity with a direct causal link.' Note: Due to the challenges and potential legal implications involved in proving a causal link between a business activity and impact to the natural world, within this document we assign impact via the IBLG (Internal, Bordering, Landscape, Global) approach, which does not consider the causation link but rather impact/s (reported values) within set spatial delineations.
Ecosystem	A dynamic complex of plant, animal and microorganism communities and the non-living environment, interacting as a functional unit (CBD, 1992).
Ecosystem Asset/s	A form of environmental asset that relates to diverse ecosystems. These are contiguous spaces of a specific ecosystem type characterised by a distinct set of biotic and abiotic components and their interactions (UN, 2021).
Ecosystem Condition (Ecosystem Integrity / Ecosystem Health)	The quality of an ecosystem as measured by its abiotic and biotic characteristics. Condition is assessed by an ecosystem's composition, structure and function which, in turn, underpins the ecological integrity of the ecosystem and supports its capacity to supply ecosystem services on an ongoing basis (TNFD, 2022, Adapted from: UN, 2021).
Environmental Asset/s	The naturally occurring living and non-living components of the Earth, together constituting the biophysical environment, which may provide benefits to humanity (UN, 2021).
Ex-situ Data Solution	Nature-related data solutions that do not require any field collected data (in-situ data) but rely almost fully on external data sourced remotely or from existing secondary data sources (e.g. satellites, models).

First-Generation Biodiversity Solutions	An approximate term used to refer to any current data solution, tool, platform, etc. (2022 and prior) used for nature-related insight. These tools, platforms and approaches can broadly be considered the first generation, the initial developments in the space.
Second-Generation Biodiversity Solutions	Still to emerge (post 2023) second generation solutions achieve improved nature-related insight at the asset level, most probably through increased access to more robust observational and asset data, and improved standards and data infrastructure.
Geospatial ESG	The use of geospatial data to generate ESG-relevant insights into a specific commercial asset, company, portfolio or geographic area (WWF; World Bank; Global Canopy (2022)).
Habitat	The area, characterized by its abiotic and biotic properties, that is habitable by a particular species (Keith, D et al., 2020).
IBLG Impacts (Internal/Bordering / Landscape/Global Impact/s)	A spatial division of nature-related insights into results within the property, internal (I), bordering (B) the property ($\leq 1\text{km}$ from the property), within the landscape (L) (1–1000km from the property or to a stated jurisdiction, e.g. a water basin) and globally (G) ($\geq 1,000\text{ km}$ from the property – such as GHG emissions). Developed by WWF's Conservation Intelligence (CI) team and used within this document to consistently and without bias delineate and assign direct and indirect cumulative impact/s to an asset without the need to prove or imply causation.
Impact/s	An attribute event, either natural or human-made, that adversely alters the status of an ecosystem's condition. TNFD, 2022 uses the following definition: 'Changes in the state of nature, which may result in changes to the capacity of nature to provide social and economic functions. Impacts can be positive or negative. They can be the result of an organisation's or another party's actions and can be direct, indirect or cumulative.'
Indirect Impact/s (Reductive Impact/s)	Impact/s that without significant habitat destruction damage, degrade or undermine in some way the ecosystem condition, either for a given area or ubiquitously (e.g. GHG emissions causing global climate change). TNFD, 2022 uses a different definition, not applied here due to issues around proving causation: 'A change in the state of nature caused by a business activity with an indirect causal link (e.g. a change indirectly caused by climate change, to which an organisation's greenhouse gas emissions contributed).'
In-situ Data	Nature-related data, or other data, collected from the field, within or near ($\leq 1\text{ km}$) to the assessed variable (e.g. species monitoring, water samples, smart meters, etc).
In-situ Solutions	Nature-related data solutions that fully or partially rely on primary or secondary data collection from the field, within or near ($\leq 1\text{ Km}$) to the assessed variable (e.g. species monitoring, water samples, smart meters, etc).
Metric/s	Results, or data, providing a form of measurement.
Nature	The natural world, with an emphasis on the diversity of living organisms (including people) and their interactions between themselves and with their environment (Díaz, S et al., 2015).
Observational Data/sets	Geospatially defined data, used to provide insights. Within this document we focus on observational data which, combined with asset data and other data points, can be used to generate metrics to support insights into biodiversity and ecosystem impact. However, a broad range of observational data can be applied and fused with other data types for additional insights into other topics.
Portfolio (Portfolio-Level)	A collection of parent companies, and their respective share within a group, forming the 'portfolio' typically held by portfolio managers.

EXECUTIVE SUMMARY

To address the interlinked climate and biodiversity challenges, the financial sector needs data accurately defining the historic and ongoing biodiversity impacts of any given asset, company, portfolio, etc. week on week, relative to its peers – to enable meaningful differentiation.

Due to the technical difficulty in providing ‘true’ ecosystem and biodiversity impact without ‘in-situ’ (ground-collected) data, current first-generation geospatial ‘biodiversity’ tools and platforms have effectively evaded the challenge by providing alternative proxy insights – insights which do not actually define the immediate and cascading impacts of a given asset on the surrounding ecosystem condition and the health and trends of the immediate and wider biodiversity over time. The challenge now, considering the likely 3–5-year time lag in collecting and aggregating in-situ data at a global scale for ESG applications, is to find robust methods with ex-situ data alone. Considering the global scale of the application, this essentially leaves one existing data option: satellite remote sensing data.

Within this document we explore the topic holistically, looking at how **improved ‘ecosystem and biodiversity’ insights can be gained, and could be consistently produced, for every commercial asset on Earth, with geospatially driven ex-situ data approaches.** This data can then be blended with other ESG data points for individual project finance or summed to parent, portfolio or area (e.g. state, nation). **Proposed methods are presented within the context of the wider policy and technical realities, showing that such insights are unlikely to organically scale without developing the necessary supporting public good data infrastructure to allow the flow and integration of data types across a diverse range of stakeholders.**

The report makes several key methodological contributions and, recognizing that data and models will evolve, outlines various data-agnostic concepts for discussion.

- 1. ‘Geospatial Asset Screening’ should adhere to an agreed standard** – To remain systematic in structure across products and to help remove the complexities around ‘causation’ (e.g. proving that a specific commercial asset caused a particular environmental impact), we propose using fixed area delineations – specifically, defining the values reported for any given observation dataset or model within the internal property of any given asset (I); the bordering area near to the asset, based either on a ratio or fixed distance/s (B); within the landscape (L) (e.g. within the water basin); and globally (G) – the IBLG model. Importantly, we propose methods for developing landscape condition metrics (L) to adjust the impact of values reported within IB values to the wider landscape situation.
- 2. Impact should be simplified and measured directly** – We divide ‘impact’ of any given asset within its IBLG spheres into direct (habitat clearance) and indirect (all other impacts than direct habitat clearance). This simplifies the equation to its absolute, to prioritize and separate habitat loss, aligning to the ex-situ data realities, where habitat clearance is often easily detected via Satellite Remote Sensing (SRS) approaches.
- 3. Methods for the quantification of ‘biodiversity’ impact needs to be agreed** – here we suggest that until the science and the aggregation of in-situ data into the equation improves, the most readily practical approach is to apply peer-to-peer percentile comparison: simply comparing assets to one another, adjusted for relevant additional factors (e.g. production volume, ecoregion, biomass, landscape condition, etc.). However, this, approach is only possible for those sectors having robust asset databases with global coverage.

Recognizing that the entire emerging field of geospatial ESG, and indeed many related fields, will remain constrained until the wider realities are factored, we suggest that there needs to be **a stepwise change in the collection, maintenance and sharing of asset, supply chain and observational data.** To overcome the current constraints in a feasible manner, we propose the development of an international ‘centre’ to oversee the creation and maintenance of a public goods data commons, best practice, benchmarking, etc., to enable the flow and integration of data across the diverse range of stakeholders from satellite to spreadsheet.

INTRODUCTION

Addressing the biodiversity crisis and climate change will shape our ability to provision the fundamentals for society, such as fresh water and sustainable food production.

As different sides of the same coin, the two issues are mutually reinforcing. Simply put, rising temperatures will exacerbate biodiversity loss, releasing more greenhouse gases, creating a negative feedback loop. This will inevitably aggravate a wide range of societal issues, from civil conflict to resource competition, in turn causing more biodiversity and climate impacts. Conversely, improved ecosystem condition and biodiversity is likely to help store and sequester carbon, support water and food security, and provide greater resilience to aid society in weathering the ongoing storm of climate change impacts.

The climate and biodiversity challenges are vast. Yet, every action taken within the biosphere – oceans, air, land and soil – matters. Our actions, no matter how small, are linked and may have cumulative negative or positive impacts on the Earth's systems.

EVERY ACTION THEN MATTERS.

Due to the scale of these challenges, effective solutions require consistent action from global society, where humanity must pull together in the same direction, making the right decisions time and time again, over decades. Otherwise, the actions of one group, or the actions of tomorrow, will undo the progress of today.

WE NEED UNITED ACTION AT A GLOBAL SCALE, DELIVERED CONSISTENTLY OVER THE LONG HAUL.

If there was no time limit – if we had all day, as it were – humanity would almost certainly move towards sustainability over decades. Unfortunately, we are under time pressure – with less than a decade to oversee a major reduction in emissions and a U-turn on our approach to **planetary biosphere management**. Solutions need to be found fast and rolled out immediately.

WE NEED PRACTICAL SOLUTIONS OPERATIONAL WITHIN A SHORT TIMEFRAME (24 MONTHS).

As the engine behind our global civilization, the financial sector has enabled scientific progression, massive increases in quality of life and many of the comforts we take for granted. It also plays the leading role in where and how we impact the natural world through the allocation of capital. How well humanity meets the biodiversity and climate challenges will be massively influenced by the response of the financial sector.

PURPOSE AND SCOPE OF PAPER:

To factor climate and biodiversity into decisions, the financial sector needs access to accurate insight into the impact of 95%+ of companies (or at least a significant majority of companies to ensure wide transparency and accountability), at suitable scales for all its varying applications. Over the last two decades, important gains have been made to aid financial actors in understanding the climate change implications of their decisions (although much work remains to be done); in contrast, however, biodiversity remains poorly understood and difficult for the sector to reconcile.

Within this paper we aim to catalyse discussion around practical ways forward to resolve the 'biodiversity data puzzle' and provide the data insight required for the financial sector.

This paper focuses on defining the impact of commercial operations on terrestrial biodiversity, via a geospatially driven approach. While we recognize that many are interested in exploring impact in marine environments or exploring other biodiversity-related topics – such as dependency on nature, ecosystem services, nature-based solutions, transition, regulatory risks and opportunities – these are outside the of scope of this paper. However, granular insight into biodiversity impact is often a preliminary insight required for exploring other biodiversity-focused topics. Critically, the technical solution proposed is data- and model-agnostic, designed to freely enable third party development, potentially across these other topics.

We deliberately make no attempt to align to any standard (e.g. SBTN, TNFD, ESRS)²; rather, we seek to define the best possible data solution for gaining accurate and meaningful insight into impact on biodiversity and ecosystems. Fortunately, there is significant organic alignment emerging, with most standards, such as TNFD, recognizing the location specificity of biodiversity and the consequent need to apply a geospatial approach. Furthermore, the approach outlined within this document can be adapted to standards and arranged to follow existing or future frameworks or classification schemes (e.g. ENCORE), if required.

While much can be done today with existing data and approaches to define biodiversity and ecosystem impact at project to sovereign scales, a significant revolution is required to move from current isolated one-off insight to having analysis-ready data embedded into existing financial systems reporting week-on-week the biodiversity and ecosystem impact for 95%+ of listed companies, including supply chain impacts.

This major step change will require a diverse range of actors to collaborate in building standards and the data infrastructure that will allow ongoing collaboration on data and methods to iteratively test and benchmark data solutions. Fortunately, this does not require novel technology; indeed, existing and ongoing developments in data capture, compute and machine learning are well positioned to support the increasing diversity of highly motivated actors keen to solve the biodiversity puzzle. Instead, the challenge will rest on how quickly and effectively collaboration can be achieved.

This document is then a call to action, raising concepts for discussion as to how collectively we might rapidly revolutionize 'biodiversity' impact insight – and help factor the externalities of these impacts into the financial system.

BOX 1 – WHAT IS IN A NAME? GEOSPATIAL ESG OR SPATIAL INTELLIGENCE?

The emerging field of applying geospatially derived insight within finance for ESG-relevant insight is sometimes referred to as 'Spatial Intelligence',³ 'Geospatial ESG',⁴ etc., and through data triangulation overlaps with other related fields such as 'Open-Source Intelligence (OSINT)' (See Page 53). Here we refer to the emerging field as 'Geospatial ESG', to place focus on the idea that this approach is specifically designed to provide insight into ESG, rather than for wider financial applications, such as predicting soft commodity prices. Although we have no opinion on or preference for any specific term, it seems probable that a single term will organically evolve for the field.

RECOMMENDED ACTIONS

We suggest the following key actions, to radically improve biodiversity insight at the scale required.

JOIN THE CONVERSATION

To push forward the concepts outlined in this document, WWF will shortly launch a 'Geospatial ESG Consortium'. We welcome financial institutions, conservation actors, tech, earth observation, remote sensing, ESG providers, etc. interested in the emerging field to join us.

CREATE A 'BIODIVERSITY DATA COMMONS'

We need to move away from siloed, standalone platforms to a 'platform of platforms' federated approach which enables improved data access and interoperability of asset and supply chain data, and observational data – integrating into the financial sector's data ecosystem.

Action – A 'data commons' needs to be established to enable actors to share critical asset and observational data, models or approaches – openly, securely or behind an FI's firewall – with robust standards. This needs to radically improve access to critical asset and supply chain data to enable assessment and, critically, the building, sharing and iteration of models and methods.

CHANGE CORPORATE DATA DISCLOSURE / ACCESS

Every asset on Earth needs to be geolocated, and accessible in either open or proprietary datasets (within the data commons). Ownership must be accurately maintained, and ideally asset datasets should be sector specific, capturing wider attributes and defining the property boundaries.

- **Action** – An 'asset registry' is needed within the data commons, uniting via a federated approach, ongoing open data disclosure and regulation initiatives. While placing the primary burden of generating and maintaining asset datasets and company trees onto the corporates.
- **Action** – Develop means to enable the sharing of supply chain data between a corporate and FI securely within the data commons.

DEVELOP AND REFINE OBSERVATIONAL DATA

Clarity needs to be created around biodiversity and ecosystem observational data, defining robust metrics. Metrics need to be tested and openly reviewed as to their ability to detect the variable under measurement.

- **Action** – The 'biodiversity' community should:
 - Align to existing efforts such as GEO BON and GBIF; provide support and iterative guidance as to which observational datasets, and the metrics derived therefrom, are scientifically robust and how they might be improved.
- **Action** – The Satellite Remote Sensing (SRS) communities should:
 - Align to existing efforts, and collectively identify spatial or temporal gaps and any possible means of improvement of the observational data portfolio, either via more regular higher-resolution data gathering or alternative solutions.
 - Explore with the wider community novel approaches, such as data triangulation, or the testing of specific novel metrics.

DEVELOP AND REFINE METHODS AND MODELS

As an emerging field, the core methods of geospatial ESG for biodiversity and ecosystem insight remain fluid. Critically, areas such as the framework, area delineations, global baselines and models determining topics such as, indirect impacts or landscape condition, need to be collectively worked through.

- **Action** – Researchers (perhaps via structured working groups) need to provide clarity on the optimal methods and approaches. Results should be peer reviewed and published when possible.

CREATE STANDARDS

Across all this work – ranging from basic arrangements for asset datasets to data security protocols – soft, technical standards need to be developed.

- **Action** – Open-source standards need to be rapidly deployed to aid developments – a large resource of existing technical standards exists which could be adopted.

ALIGN WITH CLIMATE

Many of the data needs of the 'biodiversity' space directly align with the needs of the climate space and wider ESG needs. Almost all ESG efforts, for example, would benefit from improved access to financial data, asset data and supply chain data. While eventually, since climate and nature are interlinked issues, the two will need to be considered together, as and when the data science allows.

- **Action** – Engage with 'climate data actors' early on, when developing data commons, frameworks, metrics, standards, etc., to identify opportunities for alignment.

CREATE A 'CENTRE' TASKED WITH DELIVERING THE INCLUSION OF CLIMATE AND NATURE GEOSPATIAL INSIGHTS INTO THE FINANCIAL SYSTEM

Ultimately if no-one is made responsible for the above, it is likely that progress will stagnate, with commercial actors unable to resolve the public good aspects of the equation. To ensure the work is delivered, an independent international research centre needs to be established – connected with existing efforts but tasked and resourced to ensure the delivery of SRS data, methods, models and public data utilities to aid localized, regional biodiversity and ecosystem insight and interlinked social and climate issues.

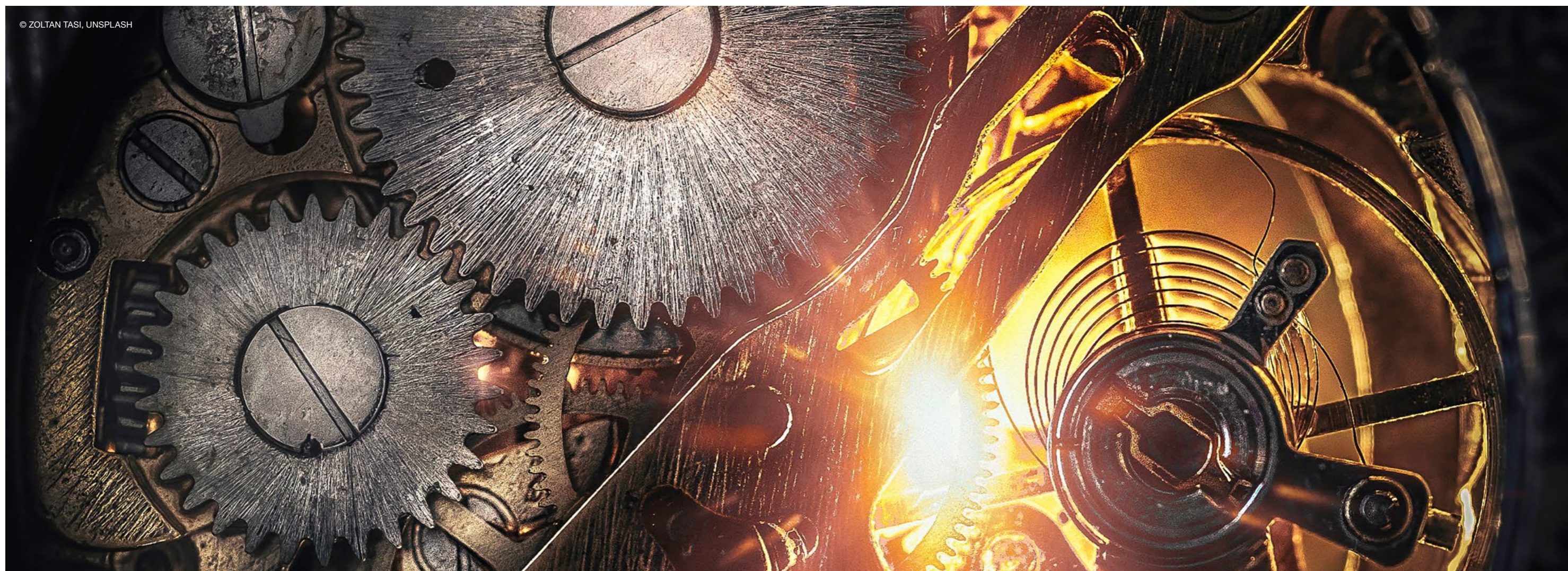
- **Action** – The government/s which take the initiative on the establishment of such a centre or federated model will place themselves at the heart of the next revolution: the inclusion, via the full weight of the SRS sector's power, of environmental and climate externalities into the financial system.

PART 1

BIODIVERSITY AND IMPACT

KEY POINTS

- The financial sector is not interested in 'biodiversity' – the variability among living organisms and ecosystems – per se but in defining the impact of specific commercial assets on changing (±) biodiversity.
- To define biodiversity trends, it is necessary to look at change within the context of ecosystem condition. Ecosystems can be simplistically thought of as complex machines, like mechanical watches, where all the parts – species – function together and cannot function apart. They are perfectly balanced to optimize the energy within that system while still being able to respond to and recover from external shocks and disturbances.
- Ecosystems face a vast range of potential impacts, from localized humanity-driven issues (e.g. habitat clearance, pollution, etc.), through natural issues (e.g. volcanoes, earthquakes, flooding) to overarching global issues (e.g. climate change), all potentially reducing their ability to function and maintain biodiversity.
- Due to impacts cascading through ecosystems, one damaged 'cog' can damage other components: removing 1 km² of a 100 km² rainforest or 1 out of every 100 species does not necessarily merely translate to a 1% biodiversity loss; over time, if a critical component, it could negatively alter the ecology and biodiversity of the entire forest (100%).
- Traditional ecology, conservation science – in-situ field research – offers the best insight into how human activities impact specific ecosystems. These field studies take significant time and resources.
- It is often challenging to translate field research into generic ex-situ models and rules for ESG insight, where thousands of models would be required to cover the multitude of possible impacts for each ecosystem, each sufficiently unique with specific localized ecology. Confusing matters, often several impacts occur on ecosystems at the same time. This variety and complexity makes defining biodiversity and ecosystem impacts and the extent of cascading and cumulative damage extremely difficult to capture with only ex-situ data.



OVERVIEW

The term 'biodiversity'⁵ has risen within the financial sector to become the byword for discussing any issue related to the natural world. In a similar way that 'climate' has become synonymous with describing any issues related to human-driven climate change.

In almost all cases, the financial sector is interested in **changes to biodiversity**, where the focus is on trying to define the impact (\pm ve) of a commercial entity (e.g. asset, corporation, portfolio, nation) on the natural world.

In short, Financial Institutions (FIs) need to know, **What is the nature-related impact of X?**⁶ Before we can begin to answer that question, we need first to be clear on what biodiversity is, what ecosystems are and how we might best measure impact on the natural world.

WHAT IS BIODIVERSITY?

In essence, 'biodiversity' relates to the green bit – the stuff that rustles, bites and squeaks. The bit we have a tough day trudging through on our latest misguided outdoor adventure. It is the wealth of 'nature' – a concept we all know intuitively. For discussions within financial applications, this loose definition, often understood as the number of animals and plants present, is enough.⁷

What is important to know is how 'biodiversity' works; from that we will be better positioned in trying to look at how we might measure impact to it.

Figure 1 – An ecosystem can be thought of as a little like a mechanical watch, where all the species, like cogs in a watch, fit and move together as a single unit. And where one change to a species, one cog, cascades through the system.

BIODIVERSITY AND ECOSYSTEMS

For financial applications, we are rarely primarily interested in the number and diversity of species present in an area, the actual 'biodiversity' of a site. Instead, we are interested in the health of those species, their trends – are they stable, going up or going down? How much damage, or recovery, is occurring? And how much of that change can be assigned to a specific commercial asset?

For that we need to look at the ecosystems.⁸

An ecosystem is a group of species which survive together. Salt marshes, coral reefs, mangroves, grasslands, rainforests and cloud forests are all types of ecosystems. Different ecosystems can occur within other wider ecosystems, such as a stream within a woodland.

Each ecosystem is like a perfectly functioning mechanical watch, each with thousands of parts – tiny springs and cogs – all fitting and working perfectly together (Figure 1). Each species is a cog within that system, **each with a defined role to play**, which often cannot be replicated as well by another species. Each is highly efficient at its role.

Over millions of years of evolution, the collection of species that make up an ecosystem have evolved together to maximize, as efficiently as possible, the energy within that system – with checks and balances to ensure stability. Designed to function in a particular medium (i.e. within a set range of temperature, rainfall, salinity, etc.), they are machines of breathtaking perfection. Inefficient species, like a chipped cog, are likely to evolve or be replaced, and in doing so often have knock-on effects – effectively subtly redesigning the whole system over time: changing the arrangement of other cogs, in turn altering other species. If the ecosystem itself naturally becomes too inefficient, or the medium around it changes too extensively, it is likely to collapse or be overtaken.

Human-altered areas of nature, such as golf courses, farmland or gardens, can contain significant amounts of biodiversity. They are, however, unlikely to be optimal or well-performing ‘ecosystems’, but more often will be a chaotic mess of species, maintained in stasis by our design, where without human intervention, the habitat would eventually revert to the ‘original’ ecosystem. Any species introduced from outside the original arrangement (e.g. garden plants imported from overseas) would most likely over the long term either become invasive, altering the original ecosystem, or die out, unable to support themselves.

Ecosystems, like a watch, are a single unit. Just as you cannot have half a fully functional watch, you cannot have half a fully functional ecosystem. Species, then, survive together in stable fluctuation, as a unit, where their survival – and the ecosystem’s ability to provide humans with essential goods and services – is entirely bound to the integrity and condition of the ecosystem/s they exist within.⁹

It is this ecosystem condition, and changes to it, which we will need to understand if we are going to be able to answer the question, “What is the nature-related impact of X?”¹⁰

IMPACTING ECOSYSTEMS AND BIODIVERSITY

Although ecosystems are often highly resilient, there are many ways to damage their functions. For example, shifting them from high diversity of species to simpler, poorer assemblages will limit their ability to function and provide wider ecosystem services.

A huge grassland once reached from France to Alaska across Siberia. Despite the colder climate than today, the ecosystem was more productive, supporting woolly mammoths, bison, musk ox, woolly rhino and giant elk. It is thought that this is because the large mammals recycled critical phosphorus and nitrogen. Through grazing they kept plant matter from being locked away in a frozen peat layer and in reach of the plants and creating a productive landscape. When the larger mammals went extinct, the decaying plant matter built up, creating an increasingly acidic peat layer, the nutrients cycle became clogged and the plants became poorer in nutrition. Today’s tundra, despite being warmer, is less productive, unable to support such large assembles of large mammals. Sadly, such phase shifts from high to low diversity and productivity are not just interesting insights from the past; they’re happening today, at increasing frequency. Perhaps the most iconic is the ongoing fate of coral reefs.

It is critical to understand that not only can we impact ecosystems, but we can damage them beyond a point of no return – resulting in ecosystems of permanently lower productivity. Indeed, the situation is so extreme that human-driven species losses are pushing close to the precipice of the sixth mass extinction, where species loss over the last century is 100 times higher than the background rate¹¹ and from which there can be no rapid recovery. We know from the fossil record that after major extinction events, the natural rebalancing and recovery of these ecosystems (and the benefits and stability they provide) is likely to take at least five million years,¹² a timescale which is meaningless to humanity.

Understanding where, how and to what extent commercial actors are damaging the natural world is then a priority, and without measurement, accountability will remain elusive. To begin to assign impact, here we simplify impacts to ecosystems into two groups: i) **direct impacts**,¹³ the loss of habitat within a given area, and ii) **indirect impacts**, impacts that, without significant habitat destruction, damage, degrade or undermine in some way the ecosystem condition, either for a given area or ubiquitously (e.g. GHG emissions causing global climate change).

Direct impacts are simple to understand, destroying part, or all, of an ecosystem, (e.g. clear felling the forest). Indirect impacts, partial damage to ecosystems, are often far more subtle but sometimes just as impactful. Indirect impacts come in many forms; some examples are as follows:

- We can damage a single part of ecosystem, one cog, or a small group of parts. We can remove one species (e.g. rhino poaching) or isolate one population from another. We can cause damage to one species, one part, which can cascade through the system causing havoc, or be absorbed and recovered from.
- We can also do the unexpected, such as introduce new parts into the watch. Introducing new species, known as invasive species, can cause all kinds of unpredictable problems and become a ‘green cancer’. Imagine jamming a new spring or cog into a watch; what would it do? It’s unlikely to make it work better, and this is the case with the natural world: new species introduced by humans across the earth have caused havoc – the extinction of native species and the breakdown of native ecosystems, which have cost billions of dollars. Two species alone, the American bullfrog and brown tree snake, are thought to have collectively caused \$16.3bn in global damage since 1986.¹⁴
- We can fragment and divide ecosystems, like pulling the teeth of cogs just a little bit too far from another to function. Fragmented ecosystems can create areas of habitat too small to support the species present.
- We can pollute natural spaces, with light, noise or chemicals, killing or injuring species, causing birth defects and lowering species breeding success.
- We can also cause indirect impact in overarching ways by globally changing the medium in which the ecosystem operates (e.g. changing the temperature or the ocean’s salinity). Ecosystems respond to these global changes by slowly shifting location over decades and centuries, moving altitude or latitude to a more suitable climate. However, if the pace of change is too fast or there is no space for the ecosystem to move to a more suitable medium, it will be lost. Such overarching pressures are also highly likely to weaken its resiliency to other threats.

Complicating the understanding of ecosystem impact is the fact that because each ecosystem is unique – its own unique ecological design and physical situation – it has its own unique vulnerabilities, which can change over time (e.g. seasonality). On top of this, impacts often combine and may grind away for decades before becoming apparent. Indeed, situations arise where environmental assets can be in what is known as ‘extinction debt’. Somewhere within the ecosystem, a function has broken (e.g. seed dispersal of a key tree species), and without conservation intervention, over time (potentially hundreds of years), it will slowly degrade from high to low diversity.

Ecosystems then can be damaged in a variety of ways – but the extent of any given impact can be hard to predict. Just as with a watch, direct and indirect impacts can cascade through the system. Happen to damage the wrong cog, the wrong keystone species, pull the wrong cogs apart, introduce parts, and the whole system can break down; at other times, the ecosystem absorbs the damage and almost nothing happens.

Damage to ecosystems and biodiversity then is not a linear percentage. Removing 1 km² of a 100 km² rainforest, or removing 1 species out of 100 within that block, does not translate to 1% loss of the rainforest’s biodiversity. It might, in time, recover and equal 0% or cascade in impact. If that block of habitat happens to be an important cog for keystone species, a breeding area or a food or water resource, this could potentially over time cause changes to the ecology and species present, across the whole forest.

BOX 2 – ECOSYSTEMS OR BIODIVERSITY?

Throughout this document we use the terms ‘ecosystem’ and ‘biodiversity’ to describe impact to the natural world. Why both? Why is it not biodiversity OR ecosystem impact?

The condition of ecosystems defines their ability to function, to maintain processes and structure, which defines the survivability of biodiversity with them. As we look to develop simple metrics for financial application, it is vital that we prioritize insight into impacts reducing ecosystem condition, as this better captures the holistic impact of an asset.

Common metrics designed around prioritizing ‘biodiversity’, such as endangered species density, often fail to capture wider changes to ecosystem condition. We can define the endangered species likely to be within a given area, but that doesn’t necessarily tell us about the wider status of the ecosystem/s. For example, there are many small islands around the world filled with endemic species; the species present, due to being found only on that island, have naturally small populations, or ranges which qualify the species as being listed as rare or endangered, creating a high density of ‘endangered’ species. And yet in some cases, the health of those ecosystems and species may be robust (e.g. the Galapagos) – it is just that they happen to be sites with extreme endemism¹⁵.

Yet of course an understanding of the biodiversity present within an ecosystem is important as it provides context for the relative conservation and genetic values of a specific site.

Consequently throughout this document we refer to both, ‘ecosystem and biodiversity’, acknowledging that we must first understand ecosystem condition while framing those insights within an understanding of the biodiversity present.

To manage expectations, it is difficult to define ecosystem condition with ex-situ data alone, and impossible to gain robust insight into all the hyper-detailed components of biodiversity change within a given site without in-situ data. The practical reality is that global scale ESG insights will be limited to high-level overviews of landscape condition and averaged proxy metrics for ‘biodiversity’. However, as we’ll show, this is perhaps the right level of detail to begin to identify across millions of assets those with higher (concerning) nature-related exposure and impact.

HOW MUCH DAMAGE CAN WE REALLY DO?

Earlier we discussed indirect impacts, noting that the removal of just one species can cause damage to the ecosystem. Often it is difficult for people to understand the true extent of damage one minor change can bring, so we provide an example. Sea otters (*Enhydra lutris*) were once widespread; as a result of being hunted for their fur in the 1700s and 1800s, their numbers plummeted. In the North Pacific, otter absence led to an explosion in their prey, sea urchins, which overgrazed the kelp forests, reducing them to what is known as urchin barrens – areas of far lower species assemblages (Figure 2).^{16,17}

With the collapse of the kelp forests came the loss of the biodiversity and the ecosystem services provided – such as food provision, dampening of wave propagation and mitigating associated impacts such as coastal erosion, sedimentation, etc. Now research is showing that the massive calcareous reefs built by algae over thousands of years within the kelp forests are now rapidly eroding due to massive overgrazing by sea urchins, at rates worsened by climate change impacts.¹⁸

Sadly, collapse brings with it not only significant biodiversity loss but often severe long-term socio-economic consequences. The Aral Sea in Central Asia was once the world’s fourth largest inland lake, a significant fishery and agricultural region. Water division and overextraction led to declining water levels and more concentrated pollution within the lake (Figure 3). Fish stocks collapsed, as did the ability to support agriculture in the region. Economic ruin followed, and the mass migration of the local population away from the once thriving region. Today, dust storms generated from the dried lakebed sediments laced with pollutants pose a public health hazard and further degrade the surrounding soils (Figure 4).

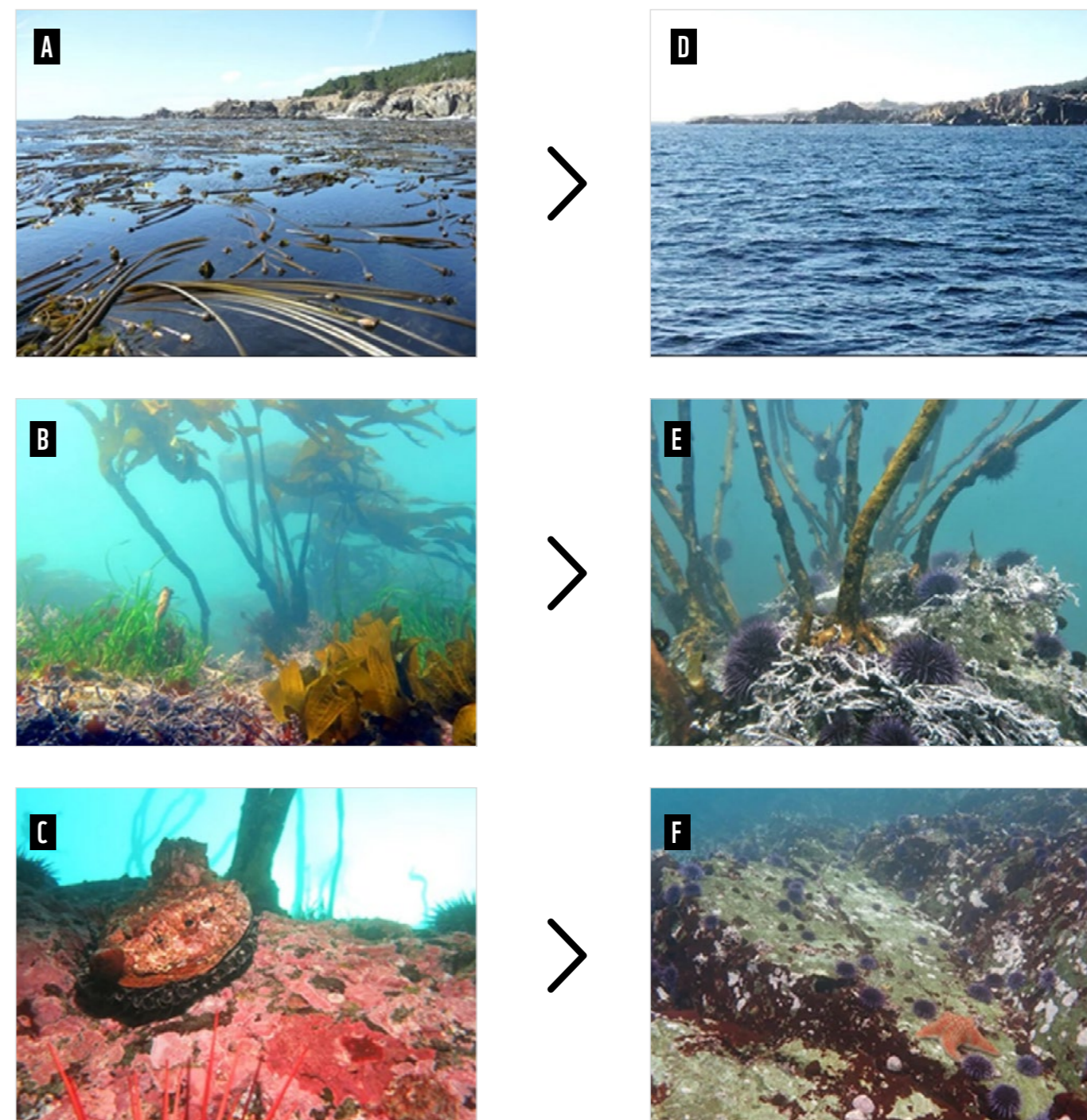


Figure 2 – From Rogers-Bennett et al., 2019; photos showing the ecosystem shifts observed for kelp forest canopy (top), subcanopy (middle) and benthose (bottom), pre-impact (a–c) and post-impact (d–f). Photo credit: CDFW (K. Joe (a,c,e); L. Rogers-Bennett (b); C. Catton (d,f)).

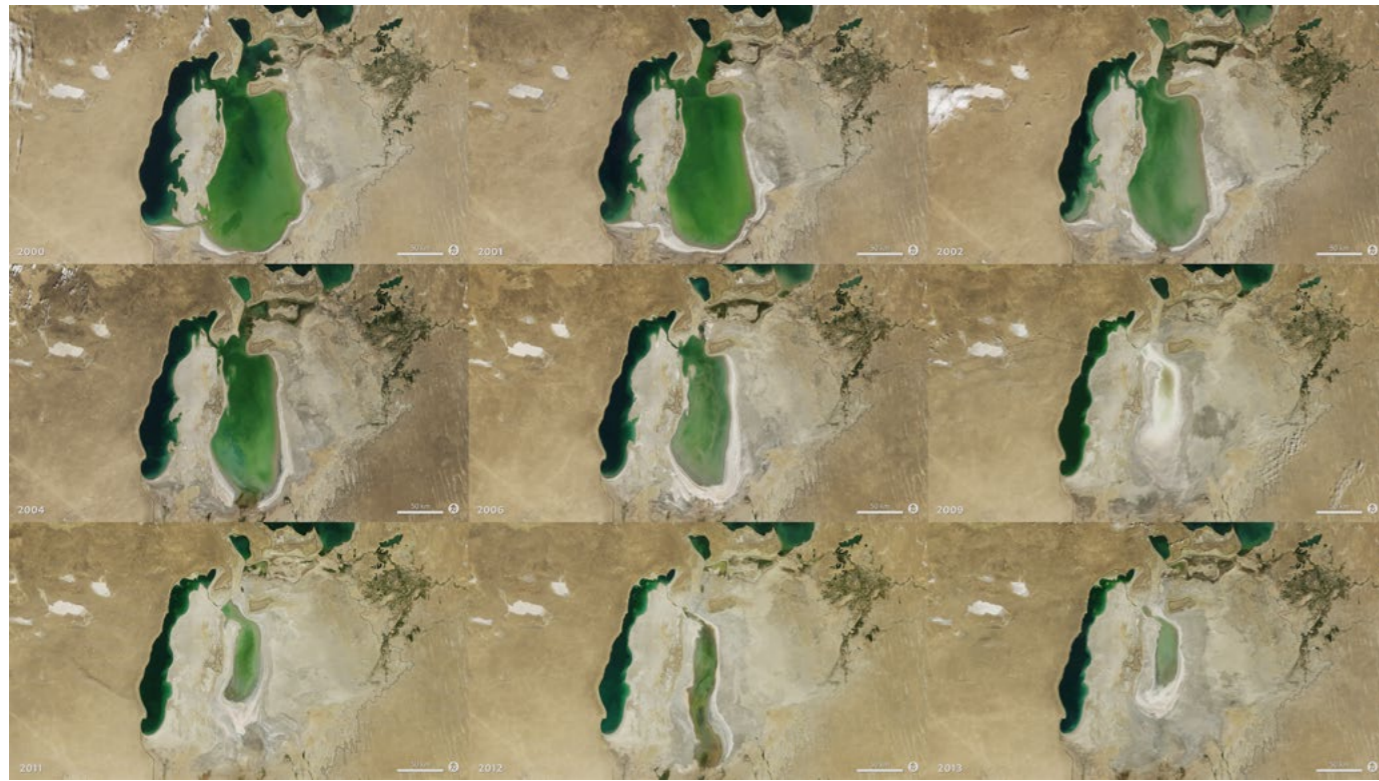


Figure 3 – Nine MODIS images showing the extent of the Aral Sea from 2000 to 2013.¹⁹

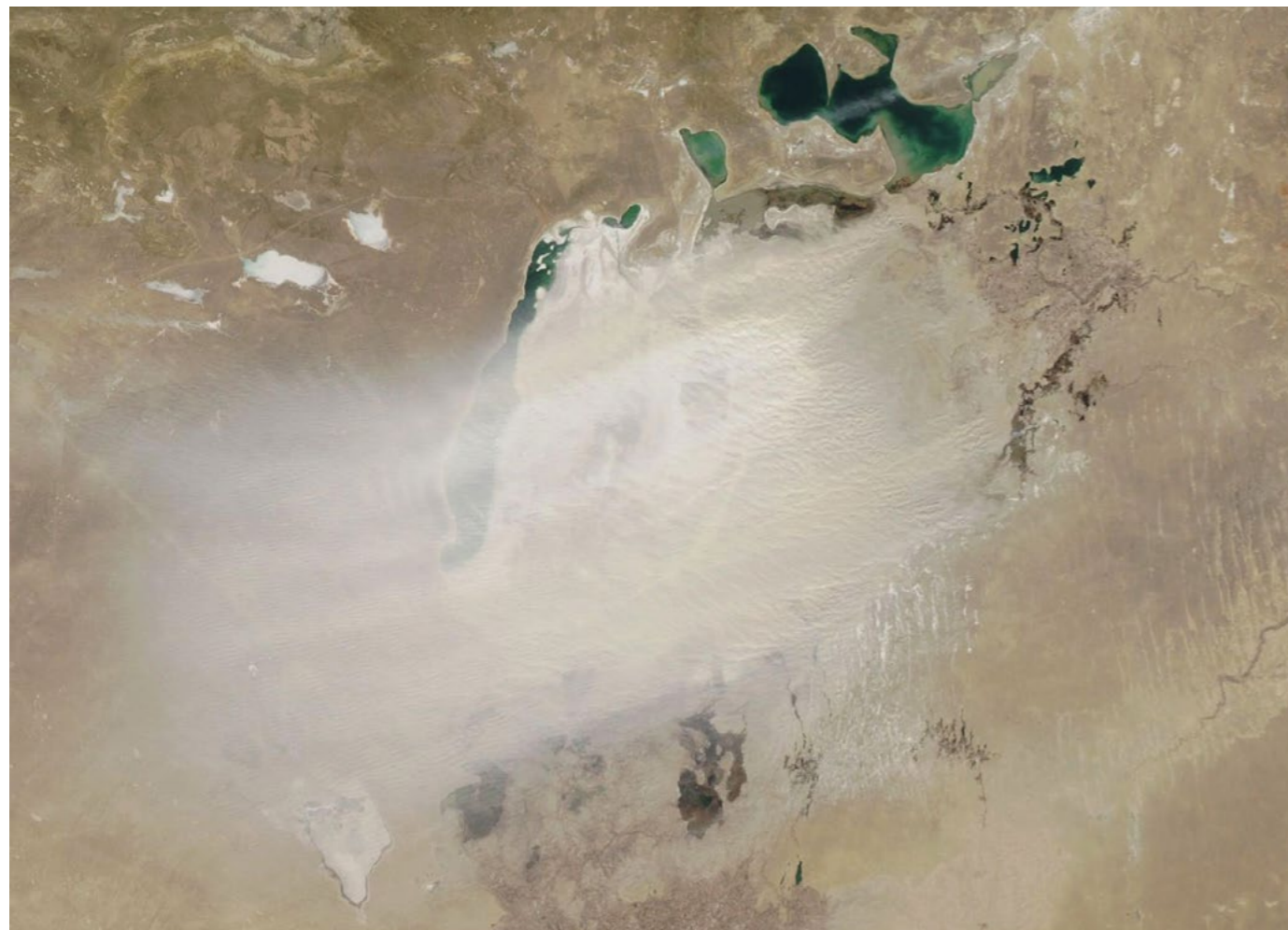


Figure 4 – A satellite image taken March 24, 2020, showing how the Aral Sea, once a giant body of water, is now a source of pollutant-laced dust, an ongoing public health hazard and continuing to degrade the fertility of soils in the surrounding area.²⁰

The story of the Aral Sea is sadly iconic, and often it's all too easy to dismiss the issue as Soviet era mismanagement, something which couldn't happen again. Unfortunately, as we move into the climate change era, tolerances for ecosystem mismanagement will decrease – and the likelihood for major ecosystem collapse increases dramatically.

As an example, the Great Salt Lake of Utah, the largest saltwater lake in the Western hemisphere, is an important site for over ten million migratory birds – it is a regionally relevant ecosystem. It also helps support the region's economy, generating millions of dollars from tourism and mineral extraction.

It is enduring a 22-year-long drought, and water levels have now dropped to the lowest level recorded, exposing 2,000 km² of lakebed (Figure 5).²¹

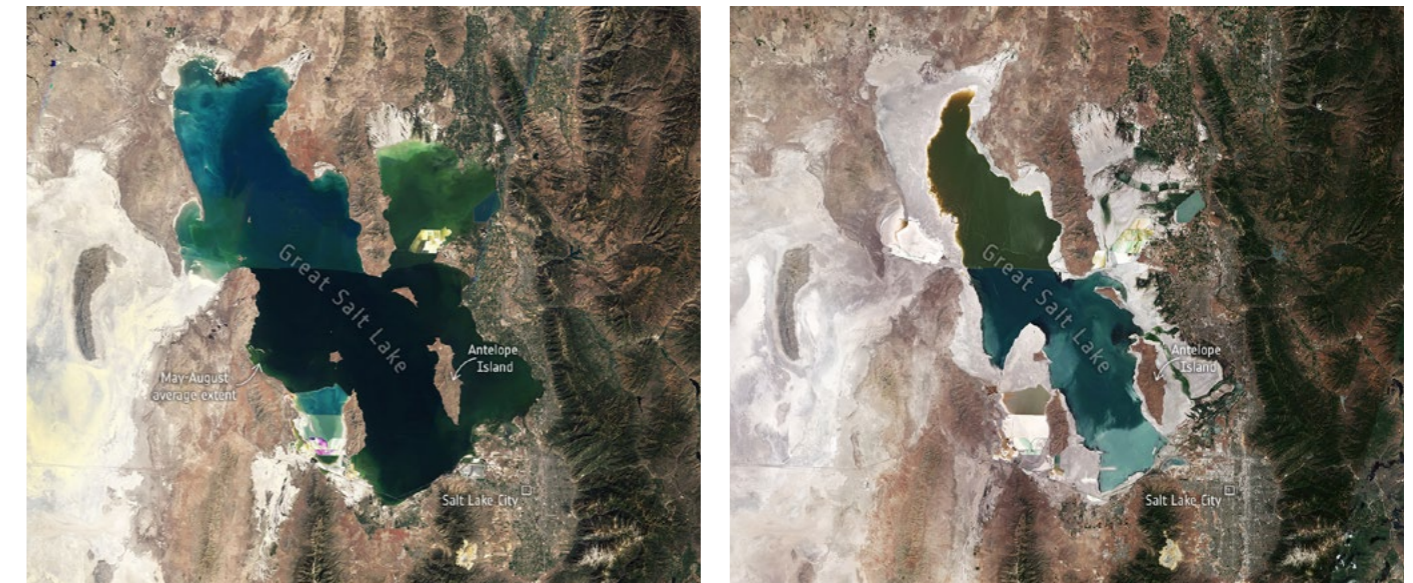


Figure 5 – Satellite images showing the 2,000 km² loss of Utah's Great Salt Lake from 1985 to 2022. Image left composite of summer acquisitions from Landsat 5 satellite; image right the Copernicus Sentinel-2 mission on July 4, 2022.²²

As the water level decreases, the concentration of pollutants (heavy metal pollutants left over from mining activity in the region) increases, as does the water's salinity. This stresses, and can kill, the shrimps and invertebrates which the migratory birds feed on. It exposes a larger area of lakebed, creating more fine dust pollution – which, mixed with heavy metal pollutants, poses a risk to public health, causing or worsening respiratory illnesses.

While the lake goes through seasonal cycles of water loss, replenishing after the snow melt, and will increase in volume later in the year, if extraction and evaporation continue to exceed the amount of water entering the lake year on year, issues are going to escalate until the ecosystem collapses.

There is the temptation to think that the collapse of these far-off ecosystems mean little to my world or business. And indeed, one cut isn't a problem – but they add up. For example, in 2016, 40 million (76 km²) of mangrove trees died in Australia due to exceptional low sea level caused by El Nina,²³ making it one of the worse mass tree diebacks and releasing nearly a million tons of carbon into the atmosphere. The mangroves have not since recovered, aggregating climate change impacts and damaging a commercial fishery. Unhelpful, but arguably still distant; but how many dieback events, coral bleaching events, invasive species, wildfires and overextraction of ground water can there be until widescale ecosystem collapse is a problem for Australia's economy and society, and then globally?

Sadly, the issue of ecosystem collapse is not isolated but present across the globe, where decline in biodiversity is unravelling ecosystems' abilities to function. Indeed, in 2020, Swiss Re reported that for a fifth (20%) of all countries, ecosystems are in a fragile state – with over 30% of their land mass compromised.²⁴

Undoubtedly then, we are capable of and are actively destroying and crippling ecosystems – and with them, their functions that support economies and humanity.

CAN WE MEASURE BIODIVERSITY AND ECOSYSTEM CONDITION?

For decades, understanding biodiversity and ecosystem condition at scale (national and global) has been a priority for governments, NGOs, IGOs and other practitioners, where, understandably, actors have been keen to find inexpensive and practical means to generate information to inform areas for prioritizing action, monitoring performance and aiding decision making.

Broadly speaking, the world of defining biodiversity and ecosystem condition can be divided into two categories, those which use detailed field data collection **in-situ**, and **ex-situ** approaches which do not. For our application,

IN-SITU

Unravelling the extent of damage caused by any one asset (e.g. a factory, a palm oil plantation, a road), is highly site-specific and often extremely complex – often requiring months, if not years, of intensive field studies to first define the status of the original ecosystem and the species present, and then unpick the consequences of the impact.

This is because each ecosystem is unique, with unique physicality and species arrangement. Consequently, the specific location of impact is a determining factor, where even within the same ecosystem a slightly different location of impact can result in vastly differing outcomes. The time of year can also change the significance of the same impact (e.g. breeding season). On top of this, each impact is unique. No two oil spills, road developments or wildfires are the same. Complicating matters is the fact that rarely is an ecosystem impacted by a single impact. Commonly ecosystems face multiple impacts simultaneously (e.g. drought, habitat fragmentation, invasive species, selective hunting pressures, water pollution, light pollution, climate change, etc.).

For example, the Biological Dynamics of Forest Fragments Project (BDFFP) has run since 1979, looking at the impact of forest fragmentation in the Brazilian Amazon rainforest, assessing 11 sites of different-sized forest blocks (1–100 hectares).²⁶ By monitoring physical and ecological changes in the blocks after their fragmentation, researchers showed certain species became locally extinct in the smaller blocks, evidencing how edge effects²⁷ changed the forest microclimate, carbon storage, tree mortality and ecology (the species interactions). They were able to show that not all fragmentation has equal impact, varying in intensity according to edge age, number of edges, adjoining vegetation, etc. and hence showing how changes to land management of bordering habitat often creates markedly different outcomes.

The BDFFP uncovered many specifics as to how ecosystem structure and biodiversity within varying sized blocks of forest changed, when divided. It took years of detailed study, measuring the water content in leaves and the humidity on transects, assessing vegetation plots, and monitoring changes in species composition and diversity – over decades. Animals and trees can live long lives, so any impacts can take decades to play out, requiring long-term study to document how the composition of a forest has changed.

where we need insight at a global scale across millions of assets, solutions must primarily be ex-situ, as field data collection is impractical.²⁵

There are, of course, an established literature, methods and science for conducting in-situ environmental assessments studies at the project level, corporate biodiversity guidelines, etc. Here, however, we focus on the overarching conceptual challenges of determining in-situ impact from a conservation science perspective – to aid insight into the difficulties of defining ex-situ impact.

The BDFFP provides an example of how much effort and time it takes to understand one impact – forest fragmentation – in one ecosystem. And yet the learnings cannot easily be transferred to other sites. Each forest, each ecosystem, is of its own design, and consequently, responses will vary, even between areas within the Amazon. Of course, robust field studies on the specific implications of a specific development (e.g. road, dam, agricultural expansion) on a specific ecosystem, such as the BDFFP, can be simplistically translated and integrated as proxy guides into ex-situ assessments, giving generic rules, such as the extent of edge effects (e.g. 100m bordering impact), within a given forest type.

Unfortunately, long-term studies, such as the BDFFP, from which to develop ‘generic rules’ are not widely available. This is because there are hundreds of potential combinations of ecosystems and impacts, many of which have not been well studied. Those which have, like the BDFFP, require significant expertise, time and resource to extract their learnings for ex-situ geospatial insights.

Let’s consider a real-world example: the Chalillo Dam was first proposed in the 1990s in the Central America tropical forests of Belize (Figure 6). After Duke Energy moved away from the project, the Canadian company Fortis developed the dam with Chinese participation in 2002.²⁸

The dam is based on the Macal River, in the Maya Mountains.²⁹ The valley was one of the last blocks of pristine riverine habitat in Central America. Detailed field studies prior to construction, commissioned by Fortis for the EIA, were conducted over four months led by a biologist from London’s Natural History Museum.³⁰ The team documented, via in-situ field study, that the area was ‘a rare and discrete floral floodplain habitat which acts as both a conduit and critical habitat for resident and non-resident fauna and avifauna’. Tapirs (a large herbivore) used the river as a critical food cache during the dry season. Neotropical migrant birds used it as a waystation. The predicted biodiversity impacts of the dam on the valley and river were documented as ‘major, long-term and regional in extent’,³¹ arguably fracturing the Mesoamerican Wildlife Corridor.

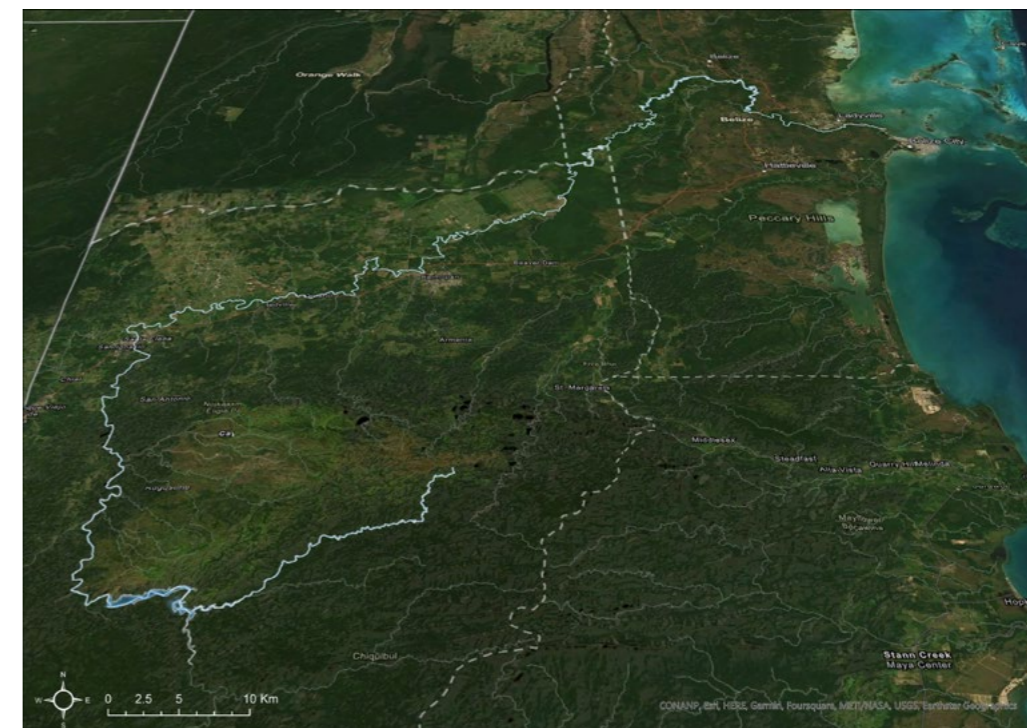
Figure 6 – Satellite image of Chalillo Dam, Belize showing the extent for the immediate area flooded.



The Chalillo Dam, whether a positive for national energy security and renewable energy generation, remains a controversial project, with disputes and issues ongoing since its construction.³²

Irrefutably it caused significant biodiversity loss, a loss well beyond the immediate area flooded, probably changing the breeding success of key species within the immediate forest, changing the wider forest ecology and changing much of the freshwater biodiversity along the entire length of the Macal River – an impact which is almost certainly being felt, along the length of the river, the forest and within local communities today (Figure 7). To truly begin to know would take sustained long-term in-situ field research.

Figure 7 – Map showing the full length of the Macal River, arguably all impacted by the Chalillo Dam, Belize.



EX-SITU

The Chalillo Dam serves to provide a rough sketch of the difficulty, even with in-situ data, in defining and quantifying the actual direct and indirect ecosystem and biodiversity impact of a commercial asset across all scales (locally, regionally, etc.).

From the ex-situ data perspective, it is more challenging still. Generalized rules cannot easily be applied, say taking the learning from BDFFP, to the Chalillo Dam, as they are sites with different species, different ecology and different impacts (flooding vs. fragmentation). Then there is the issue of biodiversity and ecosystem specificity – could an ex-situ solution have the necessary specificity to capture these hyper-localized indirect impacts, such as removing or damaging Tapir seasonal food caches? Or be able to define and assign the extent of the impact on migrating birds which pass through the region? And how could that be quantified to provide an overall comparable insight into the impact of Chalillo?

The importance of ecologically intact sites for conservation goals has long been recognized, and being able to identify and determine trends without the need for expensive and time-consuming surveys of species presence and abundance has long been an objective in the field. As a result, a large body of research, spanning decades and across disciplines, has arisen – attempting to provide ex-situ solutions into topics such as ‘ecosystem condition or integrity’. This world is complex, with overlapping terminology and methods. Approaches are varied; solutions range from generalized global scale insight, target conservation action,³³ defining intact habitat^{34, 35} or anthropogenic impact^{36, 37} to multi-metric site assessment models^{38, 39}.

Essentially, for our purposes here, it is enough to know that there are myriad approaches, some requiring the partial use of in-situ data. Different approaches have arisen in part due to different needs, but also because of disagreement on where emphasis should be placed – on different components (e.g. abiotic⁴⁰ and/or biotic), differing aspects (or combinations) of diversity (i.e. unique species, biotic communities, ecological systems, or geophysical) or on different functions, such as importance of the geophysical environment⁴¹ rather than emphasizing the maintenance of ecological functions. It is important to reflect that while conservationists will agree that ecosystem condition/integrity is essential for the protection of the natural world, the complexity of the concept⁴² has made defining the measurement difficult – and as of yet there is no consensus on a preferred approach for any specific application (e.g. conservation planning).

Perhaps one area of potential value for geospatial ESG applications, although not without its critics,⁴³ is the concept of the *ecological integrity assessment*, defined as ‘an assessment of the structure, composition and function of an ecosystem, as compared to reference ecosystems

operating within the bounds of natural or historic disturbance regimes’.⁴⁴ One example was developed by NatureServe and used to develop ecosystem-specific ecological integrity insight for wetlands and temperate forests. It is a mostly ex-situ approach that combines both biotic and abiotic values to provide insight into the ‘integrity’ of an ecosystem.^{45, 46}

As well as developing and defining new metrics and approaches, where for example Group on Earth Observations Biodiversity Observation Network (GEO BON) has been working to develop a set of twenty Essential Biodiversity Variables,⁴⁷ other approaches, designed from a different but related perspective, have looked at the question from the data collection standpoint. Specifically, a paper by Hasse et al.⁴⁸ has looked at merging two global initiatives, the International Long-Term Ecological Research (ILTER) network and the GEO BON working towards harmonizing frameworks and integrating individual monitoring initiatives centred on ecosystems – to provide insight at scale. **This development, aggregating and amassing in-situ data (and others, such as Resolve and GBIF), is of interest as in-situ data aggregated at scale are highly valuable for refining and improving ex-situ data and approaches but it also serves as a recommendation as to what variables need to be captured for holistic insight (Figure 8).**

The critical point is that significant research exists and that there are significant ex-situ data challenges in characterizing landscape condition. Of course, significant further development is required to refine and improve these approaches (metric correlation to ecological condition, quantifying relationships and transferability of metrics, etc.). That said, the geospatial ESG use case is arguably significantly less technically demanding than conservation applications, where we are attempting a high-level screening rather than the design and prioritization of conservation interventions. Current methods, or even simplified adaptations, are hence likely to be capable of providing useful insight for geospatial ESG applications. And as more data become available (via more satellites in orbit, aggregated in-situ data efforts, etc.) and more research is directed into this area and application, we can expect improved insight.

Fortunately, within the geospatial ESG approach discussed in this document, no decision needs to be made as to what components (abiotic or biotic or both) or aspects (unique species or ecological systems) need to be prioritized. As a data- and model-agonistic approach, any one or multiple approaches can be applied. New data or models can be added or older ones replaced or updated, allowing the user or a machine rationalization to make determinations as to what set of data or model is appropriate for a specific geospatial ESG application.

The next section goes into detail on the current data landscape and what approaches currently drive Financial Institutions’ understanding of nature-related impact.

E1 components and basic indicators	Recommended variables / observations	Recommended site-based instrumentation and measurement	EBV classes to be informed
Abiotic heterogeneity	Habitats	Habitat / land cover	Habitat mapping, remote sensing
	Soils	Soil moisture content /temperature	Measurement beyond the point scale, e.g., cosmic ray probes, wireless sensor network,e.g., Time Domain Reflectometry probes
		Soil texture, bulk density, pH, C _{org}	Soil inventory / basic mapping of soil physical and chemical properties
	Water	Water quality: water temperature, pH, electrical conductivity	Standard water quality probes
Air	Air temperature, barometric pressure, incoming short-wave radiation, wind speed / direction, precipitation, humidity	Standard climate station	
Biotic diversity	Fauna	... of birds	Point counts / transects
		... of butterflies	Transect counts
		...of bees	Combined flight traps
		... of ground beetles	Pitfall traps
		... of benthic invertebrates	Multi-habitat- sampling
	Species richness in soil	eDNA (environmental DNA; species detection)	Genetic composition, species populations, community composition
Terrestrial species diversity	Automated multi-sensor station for monitoring terrestrial species diversity (AMMOD); identification based on DNA metabarcoding		
Flora	Abundance of vascular plants	Vegetation survey during the phenologically most appropriate time	
Within Habitat structure	Vertical forest structure (stand height; tree height, tree diameter)	Standard forest inventory / remote sensing	Ecosystem structure
Energy budget	Concentration of CO ₂ , water vapour, albedo/ radiation budget, soil heat flux, climate variables.	Eddy-flux covariance station	
	Leaf area (Index, LAI)	LAI optical sensor	
	Primary productivity (biomass above ground)	Light Detecting And Ranging (LiDAR); use of data from forest inventory	
	Transpiration	SAP-Flow-measurement	
Matter budget	Wet / dry / bulk atmospheric deposition	Deposition samples	
	Discharge surface water; spectral absorption coefficient; DOC; nutrients	Optical sensors;multi-parameter probes	Ecosystem function
Soil water chemistry	Soil water samplers and analysis		
Water budget	Hydrological discharge; discharge, water temperature, pH, electrical conductivity	Standard gauging station including measurements of basic physical variables	
	Groundwater; level, temperature, specific conductivity	Groundwater station	
	Throughfall and stemflow	Throughfall samplers, stemflow collectors	
	Snow depth	Optical sensors	

Figure 8 – Table from Hasse et al.⁴⁹ suggesting recommended variables, measurements and instrumentation for terrestrial, freshwater and coastal environmental monitoring sites considering the ecosystem integrity (EI) and essential biodiversity variables (EBV) framework; note that while some are possible with ex-situ measurement or proxies many are not possible with ex-situ measurement.

An aerial photograph showing a transition from a palm oil plantation to a natural forest. The top half of the image shows a dense plantation of palm trees with a dirt road winding through them. The bottom half shows a lush, diverse natural forest with various tree species and a thick canopy.

PART 2

CURRENT APPROACHES TO MEASURING 'BIODIVERSITY'

KEY POINTS

- Biodiversity is increasingly important to the financial sector. It is interlinked with the climate crisis and needs to be factored into financial decision making.
- Financial Institutions are increasingly interested in understanding their 'biodiversity exposure'. Currently most of their insight comes from data produced by the corporates themselves in the form of annual reporting. Additional insight is frequently achieved through third-party data, such as geospatial and web-scraping insight, and standalone geospatial or footprinting tools.
- Due to the challenges involved (hyper-specificity, site and impact uniqueness and cascading impacts), it has proven difficult to develop scalable ex-situ data solutions that can generate sufficient specificity and precision to provide informative results that be used to effectivity align capital away from biodiversity impact.
 - A major reason for a lack of objective, consistent, comparable, pre-processed results defining ecosystem and biodiversity impact is due to the ex-situ data challenges in capturing and estimating impact for unique assets and their activities (e.g. gold mine) in unique ecosystems with unique vulnerabilities which may shift and change due to seasonality and wider landscape or global impacts (e.g. climate change).
 - In addition, there is a universal lack of access to robust asset and supply chain data to enable insight. Such supply chain data, commonly unavailable, is vital to understanding a higher tier company's impact (for example, the vast majority of an electronic chip manufacturer's impact will be in its supply chain).
- Nature-related insights remain difficult to achieve within the limits of the data available. Consequently, it may prove more effective and productive to simply improve the quality and extent of asset and supply chain data available, rather than attempt to find ever more complex means to circumnavigate data limitations for marginal gains.

CURRENT APPROACHES TO MEASURING ‘BIODIVERSITY’

Financial institutions are increasingly interested in the topic of ‘biodiversity’, where both risks and opportunities may be present. A recent Robeco survey of roughly 300 large investors (representing approximately USD 23.7 trillion) found that two years ago, only 19% of investors considered biodiversity a significant factor in their investment approach, doubling to 41% today and expected to increase to 56% in two years’ time.⁵⁰ This was commonly motivated (52%) by commitment to reducing the long-term global societal risks associated with biodiversity loss.

This perhaps comes as no surprise – the topic has long been rising on the agenda. At the regulatory level, France published Article 29 in 2021 requiring all FIs to disclose biodiversity- and climate-related risks.⁵¹ In the EU, amongst a raft of new legislation, the the Sustainable Finance Disclosure Regulation (SFDR) requires companies to disclose activities that negatively affect biodiversity-sensitive sites. The Corporate Sustainability Reporting Directive (CSRD)⁵² and the European Sustainability Reporting Standard (ESRS)⁵³ will require companies with significant operations within the EU to disclose specific metrics on the impact their activities have on biodiversity and their dependencies on nature.

To help meet the growing demand, a range of data approaches – some highly specialized, others more generic – have risen within ESG and related fields, designed to give full or partial insight into the ‘environmental’ or ‘biodiversity’ implications of project, company or portfolio. Almost all commercial and open ESG data approaches are not limited to ‘biodiversity’ but consider and often interlink wider related variables, covering bordering topics such as climate change, natural disaster risks, water risk, etc.

These data approaches are:

Corporate reporting

Frequently the mainstay of the ‘E’ pillar in ESG. Commercial ESG providers source the annual sustainability and ESG reports and other literature produced by companies themselves, aggregating this unstructured data into consistent formats and provide analysis and clear standardized scores to facilitate peer-to-peer comparison.

Surveying

Some actors interview companies to gain ESG-relevant insights, often through a structured questionnaire. Normally these are conducted annually; CDP, for example, reviews six questions on biodiversity topics.⁵⁴

Unstructured Content

Specialized data providers web-scrape media articles from the internet, often applying machine learning to identify positive and negative news stories about projects and companies. Often reviewing tens of thousands of articles a day in multiple languages, they combine these data points with other ESG data points to provide ‘E’ scores for thousands of companies.

Geospatially driven

Using a location point, either exact or regional, these assess company operations against observational data to provide insight into possible environmental implications (e.g. deforestation). To date, the approach tends to be designed around screening for project finance, often without pre-packaged asset data, requiring the user to upload and compile their own asset data and assessment. Examples include Global Forest Watch Pro,⁵⁵ Ecometrica,⁵⁶ Maphubs⁵⁷ and Integrated Biodiversity Assessment Tool (IBAT)⁵⁸. Others, such as Asset Resolution,⁵⁹ Verisk Maplecroft⁶⁰ and Reprisk⁶¹, contain asset data and can in some cases provide insight at asset, corporate and sector levels. Major business intelligence (BI) providers are also increasingly integrating geospatially derived assessments, to explore nature-related topics.

Hybrid approaches

Increasingly data providers are blending the above data approaches, and additional methods not described, to gain improved insight.

Alongside these data products, a range of standalone biodiversity measurement platforms and data tools have emerged to support the private sector in running their own biodiversity impact and dependency assessments. These tools are often designed around corporate use for internal assessment but can be applied by financial institutions for additional biodiversity performance insights into corporates or portfolios.

Biodiversity measurement tools

A vast and growing range of standalone tools and platforms, some in part drawing from geospatial datasets, have arisen to help corporates assessing the biodiversity impact or dependency of their operations. There is a wide universe, from life cycle assessment tools to localized sector specific tools. Here we focus on those more applicable to global-scale financial application. These tools often require user inputted data (e.g. sales per segment, total revenue, emissions, sector/s, location; often to model production/consumption using input/output tables) and combine it with additional external data. They are mostly used at the product, project, supply chain and, to a small extent, corporate level. Examples include:

- Biodiversity Footprint Financial Institutions (BFFI)
- Product Biodiversity Footprint (PBF)
- Species Threat Abatement and Restoration metric (STAR)
- Biodiversity Net Gain Calculator (BNGC)
- Biological Diversity Protocol (BDP)
- Corporate Biodiversity Footprint (CBF)
- Global Biodiversity Score for Financial Institutions (GBSFI)
- Global Biodiversity Score for Companies (GBS)
- Exploring Natural Capital Opportunities, Risks and Exposure (ENCORE)

These tools commonly incorporate a footprint modelling component that converts publicly disclosed revenue figures into production volumes as a starting point to scale biodiversity impact. To achieve this, they classify the various activities of a 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, CO₂ and CH₄ emissions, and freshwater pollution. These are then often converted again into biodiversity impact metrics, such as Mean Species Abundance (MSA) via an open-source model, such as the Global Biodiversity Model for Policy Support (GLOBIO), or Potentially Disappeared Fraction of Species (PDF) via the ReCiPe model.⁶²

CONSIDERING THE CURRENT DATA LANDSCAPE

A useful starting point from which to consider the biodiversity data puzzle is to look at the current ESG data landscape. It is timely to stress here how similar the 'climate' and 'biodiversity' data spaces are, using the climate data ecosystem as outlined by Climate Arc (Figure 9).⁶³

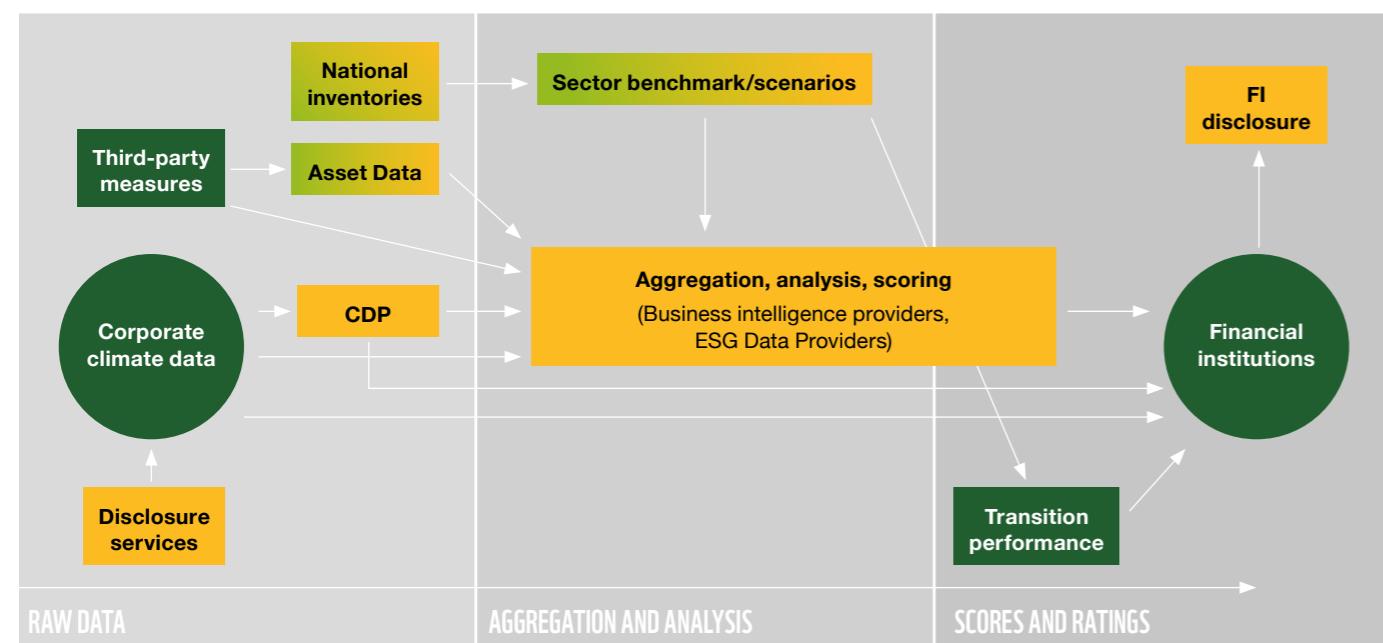


Figure 9 – Simplified version of the climate data ecosystem from Climate Arc, 2022. ■ Restricted Information ■ Public Information

If we add the 'biodiversity' components (Figure 10), we see an essentially unchanged landscape.

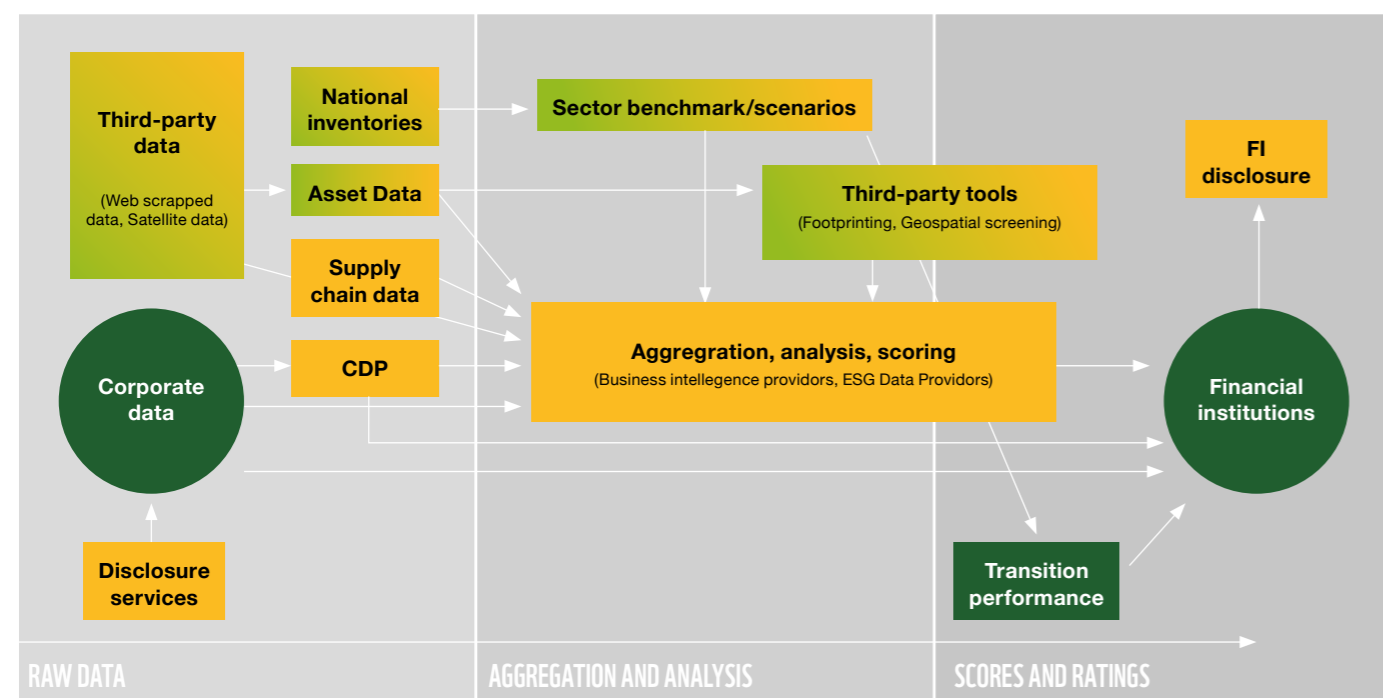


Figure 10 – Simplified adaption of Climate Arc data landscape, adding 'biodiversity' components, to illustrate how most data used for nature-related insight used by FIs flows from the corporates themselves via annual ESG reporting in public and grey literature, through ESG data providers, into the FIs. However, some FIs make major efforts to also use third party data and tools and internal systems to triangulate results.

While of course the 'biodiversity' space does not use national inventories or transition performance and has a wider range of standalone data tools outside of the mainstream ESG space – **the major flow of data from corporates themselves into commercial data aggregators is similar in structure.**

Within the 'biodiversity' data ecosystem, a significant volume of the data comes from the corporates themselves in the form of documents (e.g. annual sustainability reports). ESG data providers ingest, aggregate, clean and analyse these publicly released documents to provide insight. In many cases they combine this data with additional third-party data, such as web-scraped news insights. Unlike the climate data space, the biodiversity space does not have a dedicated actor, such as CDP, tasked with systematically collecting biodiversity impacts insight (although CDP does collect some data on biodiversity⁶⁴).

There are four key points about this current data flow:

1. The 'biodiversity data ecosystem' aligns to the 'climate data ecosystem' with no significant change in structure.
2. The core of 'E' in ESG data used by FIs comes from commercial ESG providers – who base their results upon annual reporting and surveying which have a low cadence, updated once per year.
3. Additional data, such as geospatial and web-scraping insight, is often used to complement the aggregated annual reporting within commercial ESG solutions to provide higher-cadence insights. However, such data points are often – from an ecosystem impact perspective – inconsistent in capturing impact (e.g. heavily biased towards sectors with asset data, or those impacts which happen to be reported in the media).
4. Additionally, FIs, often independently of commercial ESG solutions, source additional, often targeted, insight via standalone geospatial asset screening platforms and biodiversity footprinting tools. These tools tend to be used for niche applications and are typically not integrated with or across the mainstream ESG-provisioned data. These solutions often are unable to provide insight for a large percentage of companies, lacking the necessary asset data, or are simply designed for individual company assessment.

In the final section of this document, we will reflect again on this data ecosystem.

CONSIDERING COMMERCIAL GEOSPATIAL ESG DEVELOPMENTS

Perhaps galvanized by TNFD⁶⁵,⁶⁶ and ESRS⁶⁷, both of which have increasingly promoted the need for locating companies' operations for 'biodiversity' insight, MSCI,⁶⁸ Moody's⁶⁹ and others have released short articles on the topic. As an example of some of the issues these current approaches take, let's look at MSCI.

It is important to state that any limitations identified or inferred in MSCI's approach are primarily the result of simply not enough robust data being available – and are ubiquitous issues present across open and commercial ESG solutions and not unique to MSCI.

MSCI's geospatial approach for biodiversity insights used the Mean Species Abundance (MSA) metric for 2015, from the Global Biodiversity Model for Policy Support (GLOBIO), as a proxy for local biodiversity intactness.

They state that, 'Biodiversity-sensitive areas are intact ecosystems with minimal species loss that are important areas for conservation efforts and are more sensitive to biodiversity-loss impacts.' They go on to state, '...an asset in an area with an MSA value over the global average of 0.56 is considered to be in a location that is more sensitive to adverse impact.'⁷⁰

They found that 4,603 assets were located in a sensitive area, defined as an area with a score above 0.56 (0–1), the global area weighted mean for 2015 (Figure 11 on the following page).

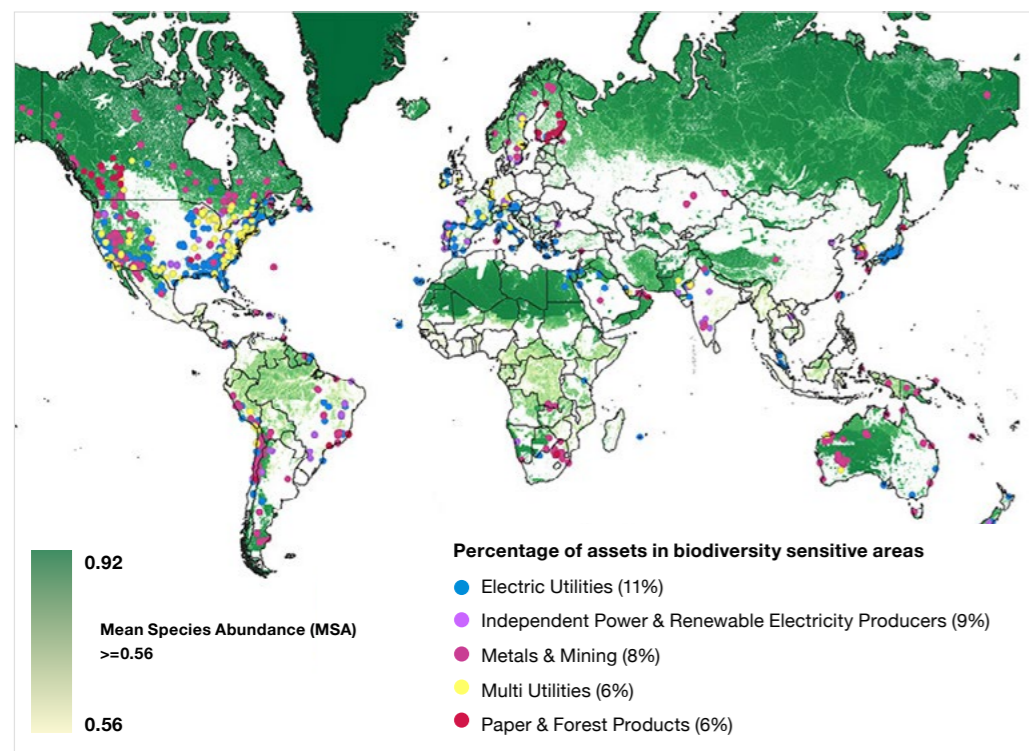


Figure 11 – Map from MSCI effectively showing the overlap between MSCI’s asset location data and Mean Species Abundance (MSA), indicating the local biodiversity intactness, derived from GLOBIO data as of 6th April 2022.⁷¹

The challenge here is that while the GLOBIO model is an excellent, highly scientifically robust model, on a specific asset-by-asset screening, the extent of human activity, or anthropogenic pressure, within an area, is not necessarily related to that specific asset’s actual ecosystem or biodiversity impact, nor even its risk of impact. Naturally, it is highly undesirable for any remaining large areas of wilderness to be fragmented or developed. However, it creates the potential that results will be misinterpreted, that areas with higher scores, are ‘more’ sensitive to adverse impact and are the only areas sensitive to impact.

A site which is surrounded by development with very low intactness can still be of extreme biodiversity importance. The Brazilian Atlantic Forest, of which only 11% of the original range remains, is heavily fragmented, (240,000 blocks, average size 64 ha).⁷² It is the last outpost for tens of thousands of species. The far larger neighbouring Amazon Forest of higher intactness (~68% remaining, 80,000 fragments, average size 8,376ha)⁷³ is arguably ‘less’ sensitive to impacts since the Atlantic Forest is already under arguably higher pressure, and further impacts are likely to have larger ramifications for the survival of that ecosystem and the species present than an equal area in the Amazon. Of course, commercial activity in either forest is highly undesirable – but the point is that on an individual asset level, operating within sites of a lower level of ‘intactness’ isn’t necessarily preferable, particularly if the ecosystem of higher intactness occupies and extremely large area and has extremely low biodiversity richness.

The second and far more pressing issue is that MSCI’s approach, and indeed many first-generation ‘nature-related’ approaches, is that it uses proximity to ‘biodiversity’ as a simple way to infer impact or risk of impact. Unfortunately, as correlation does not imply causation, **proximity does not imply impact**. Simply being near to the forest is not indicative that the asset is causing an impact. Likewise, being located far away from nature does not guarantee less impact. Commercial operations can and have polluted waterways that have destroyed biodiversity hundreds of miles downstream. The acid rain caused by emissions emitted from UK factories pre-1988 legislation travelled hundreds of kilometres across the ocean to harm the forests and waterways of Scandinavia. Such an approach risks biasing impact heavily on those industries which, by the nature of their operations (e.g. farming, mining) more frequently rurally located.

In an attempt to get around this issue, many approaches apply weighted industry scores, giving higher scores to those industries and processes with known higher potential for environmental impact/s. However, as we seek to determine peer-to-peer performance, this is potentially unhelpful. For example, all mines, or even of one type – say all open pit gold mines – are not equally well managed or operated; exist across sites with differing resilience with differing level of biodiversity present; hence, their biodiversity impacts are unique and specific. **What matters for financial application is understanding the ecosystem and biodiversity impact for each asset individually – within the property, bordering the property, regionally and globally (with GHG emissions) – across both their primary assets and suppliers’ assets. This is what is required to enable the accurate differentiation between peers.**



Maxar WorldView-2 color infrared satellite image of Hyderabad, India, highlights healthy vegetation in red. Image collected on May 12, 2014. Satellite image © 2022 Maxar Technologies.

REFLECTIONS ON CURRENT CHALLENGES

Despite the ever-growing complexity in 'biodiversity' data products, a major gap remains – objective, consistent, comparable, pre-processed results, defining the ecosystem and biodiversity impact for 95%+ of companies including their supply chains.

A simple way of demonstrating the extent of the issue is to ask which solution can currently satisfactorily answer the hypothetical question, **Which has a greater ecosystem and biodiversity impact, BMW or Mercedes?**⁷⁴

Which tool, platform or data product currently provides ready-to-go results, **without user inputted data** – a detailed, regularly updated (weekly) insight into the granular nature-related impacts of these companies, or any major company, including supply chain impacts?

Unfortunately, it's very difficult, and here's why:

- Biodiversity is highly site-specific. As a result, highly granular data on ecosystem and biodiversity and the company operations are required in some form to understand their interaction and trends over long time frames (10 years +). Such nature-related data is often lacking or difficult to gain access to, and while the methods applied to estimate (direct and indirect) impacts to ecosystem condition are developing, they remain inconsistently applied.
- 'Commercial' impacts are extremely varied in themselves and vary in severity depending on ecosystem condition. Assessment methods need to be tailored to each activity and each site sensitivity, to be able to identify and accurately assign impact.
 - Footprint-based/modelled approaches tend to be unable to capture such specificity – applying sector averages and hence providing generic insight into 'potential' impact, rather than insight into specific real-world impact.
- Impacts can cascade through ecosystems and are often technically difficult to capture and unravel.
- Impacts frequently interact with one another within a given landscape, where multiple companies will be operating. Unravelling responsibly for a given impact is often extremely difficult.
- To address issues surrounding the tragedy of the commons – where each actor does a small amount of damage, but collectively over time the damage aggerates (cumulative impacts) within the ecosystem – additional landscape and jurisdictional data are required for context.
- Impacts are constantly occurring: small-scale marine oil spills occur every day; small blocks of habitat are destroyed each day. Data with high cadence is required to both capture impacts which have a short exposure time (e.g. methane pollution) and support timely insight.
- Asset data defining the location of company operations is often unavailable, making it difficult, sometime impossible, to run geospatial driven assessments.
- Data defining supply chains (and their location) is often not disclosed – a data shortfall that has proven difficult to fill even with efforts by commercial data providers. Since the biodiversity impact of high tier industries is often almost entirely within their supply chains, their inclusion is vital.
- From a geospatial data solution perspective, current limitations on availability of observational data creates bias and error within current data solutions – where, for example, a lack of data drives 'temporal false negatives' (See Page 48).
- Lacking robust data encourages the uptake of proxy indicators, such as proximity of the asset to a protected area, the significance of which from an ecosystem impact standpoint is often difficult to determine.
- Quantifying the huge diversity of 'biodiversity' impacts into a single unit of measurement (cf. a ton of carbon) – is technically extremely difficult, with no agreed approach or measurement unit.

CONCEPTUAL CONSIDERATIONS

A conceptual threshold exists for defining an asset's (and then corporate's or portfolio's) nature-related impact, where a level of sensitivity needs to be achieved to ensure the results are accurate enough to enable accurate insight and differentiation (Figure 12).

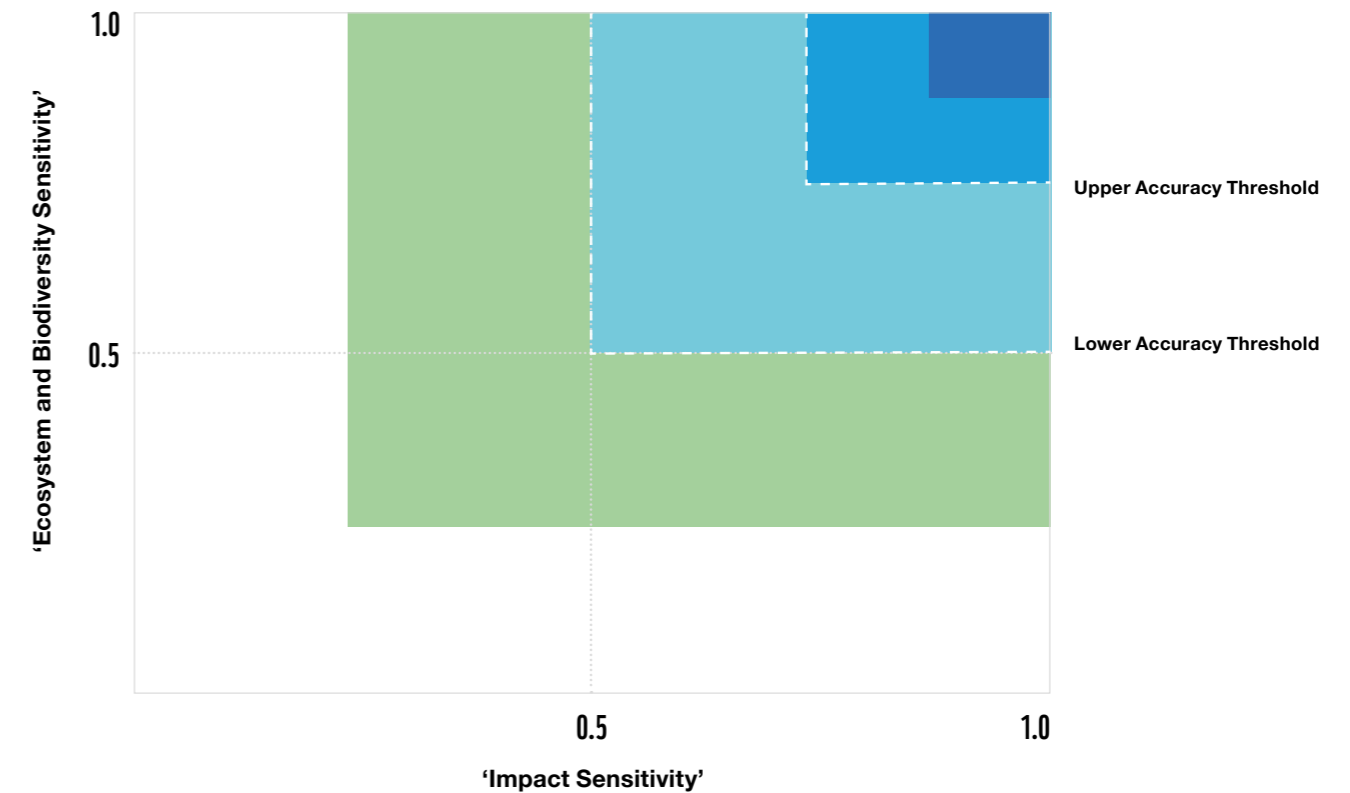


Figure 12 – Diagram illustrating the concept of accuracy thresholds for ecosystem and biodiversity impact insight.

Solutions must have a robust level of impact detection, capable of predicting or identifying and correctly assigning the majority of a commercial operation's impact to the correct holder. They must then be able to adjust those impacts at a high enough resolution to the fluctuating localized ecosystem resilience to define real-world ecosystem and biodiversity impact. Results which do not capture a significant proportion of impacts and/or are unable to estimate the magnitude of impacts at a suitable level of accuracy are likely to be too inaccurate to provide meaningful insight. They will not cross the conceptual accuracy threshold (Figure 12). Conversely, since no solution will be perfect, a conceptual upper accuracy threshold exists (Figure 12).

Within this space, differing but related applications have divergent accuracy thresholds. For example, the emerging 'biodiversity credits' and offshoot of 'carbon credits' will, by virtue of the robust accreditation needed to capture and retain market trust, almost certainly require more in-situ data than global scale geospatial ESG screenings (Figure 13). Due to the data challenges around in-situ data for global scale assessments, we focus here on what might be achieved, at the lower end of the spectrum, without the use of in-situ data.

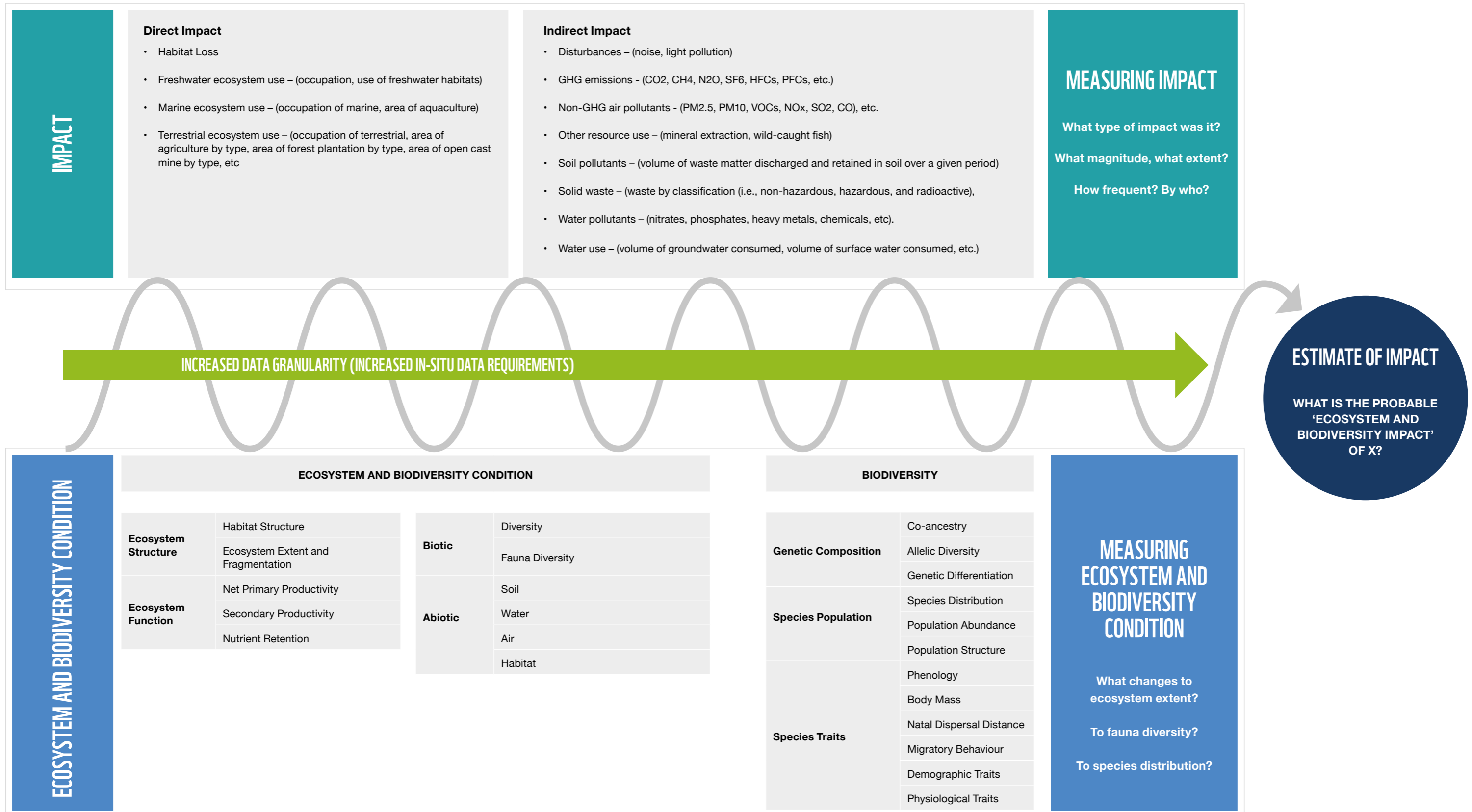


Figure 13 – Diagram illustrating the concept that two measures are required, 1) a measurement of impact and 2) a measurement of 'ecosystem and biodiversity condition' to estimate the probable 'biodiversity impact'. Different applications have differing accuracy needs, and consequently some areas will require more in-situ data.

BOX 3 – SUPPLY CHAINS AND THE EXTINCTION ECONOMY

Here it is important to reflect that the assets generating the worst impacts, per unit of production, on the natural world, are not evenly spread across the economy. They are proportionately more often within the primary, lower-tier industries, as these operations by default interact more with the natural world (Figure 14).

These assets are sometimes operated by known listed companies or governments but more often by junior, unlisted, unknown or illegal operators at the very fringes of the economy. While every asset has to some extent a nature-related impact, those outliers which have a dramatically higher proportion contribution form what could be considered conceptually as the core of the global extinction economy. These legal or illegal parts, primarily through habitat clearance, are continuing to drive humanity and the natural world towards the 6th mass extinction.

Hence, we need a means to include dynamic supply chain data, to ensure the most problematic assets, which may not be accountable (e.g. illegal operations, unlisted), are not present and enabled in any accountable listed companies' operations (via their supply chains).

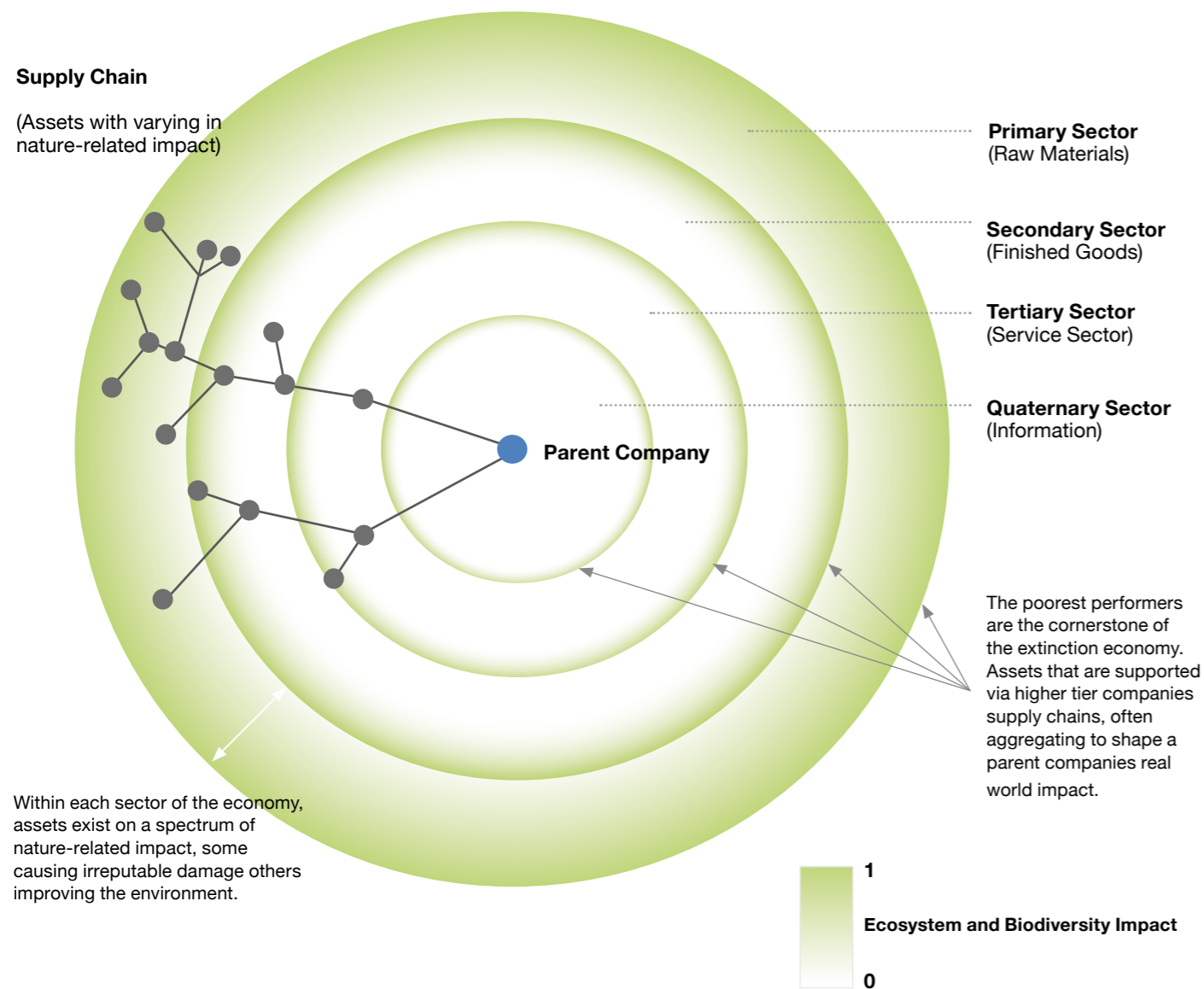


Figure 14 – Diagram illustrating the concept that impact on the nature world is unequally spread across sectors, respectively higher in lower tier industries. Yet higher tier companies, via their supply chains, fuel and profit from these operations. Consequently, understanding each asset's impact within supply chains back to source is necessary to understand a parent company's nature-related impact.

Due to its relevance in addressing the climate and nature crises, the teams which break the accuracy threshold for geospatial ESG insight will achieve a major milestone. However, only so much can be achieved with the limits of the data available, and as we'll argue, in many cases the quickest route to improved insight is to simply improve the quality and extent of data available, particularly asset and supply chain data.

The current situation is disconcerting. Doubly so, when we consider that there is a willingness amongst financial institutions to engage with biodiversity, but many report that they lack robust means to do so. For example, the Robeco survey found that **73% of investors do not have a way (a data solution) to assess impacts to biodiversity**, but equally 71% would respond if there were greater data transparency (Figure 15).

There is a lack of awareness on the financial implications of biodiversity loss.

To what extent do you agree or disagree with the following statements about biodiversity from an investment perspective?

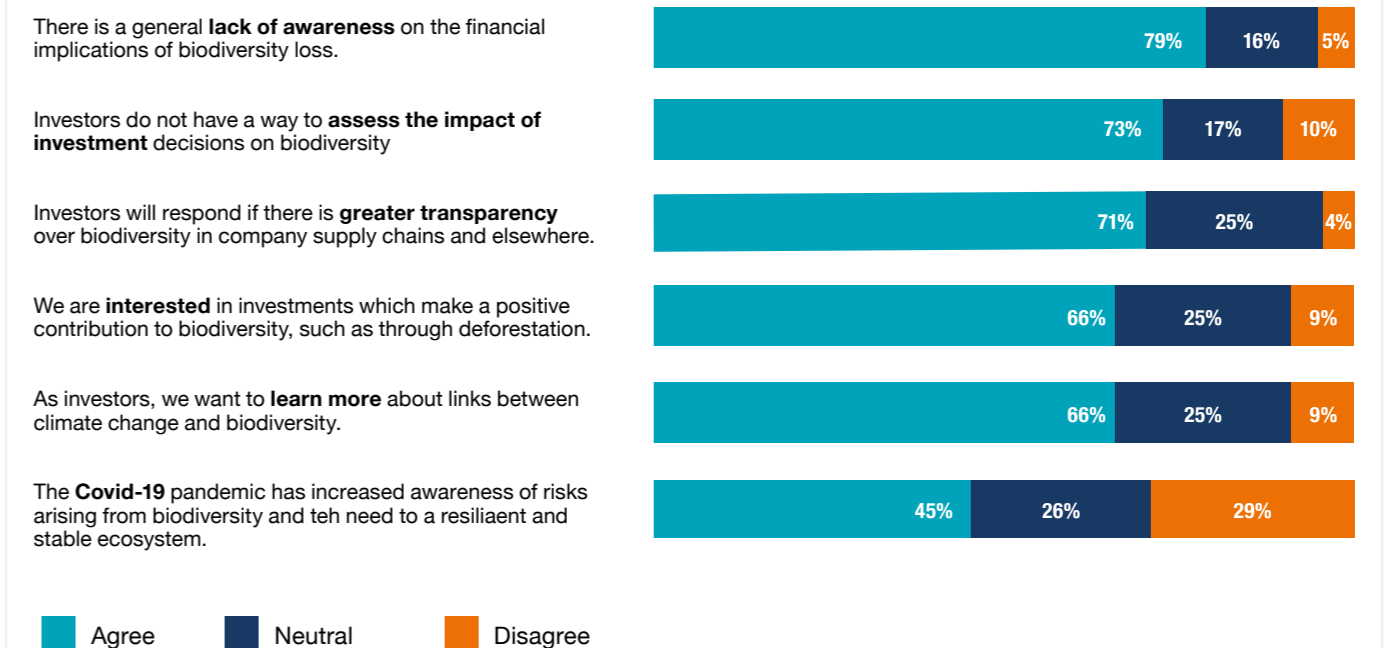


Figure 15 – Graph from Robeco, 2022, showing the results of a survey of asset managers.⁷⁵

In the next sections we look at possible solutions to the 'biodiversity data puzzle', exploring a geospatial approach to the problem.

PART 3

EXPLORING THE GEOSPATIAL SOLUTION

KEY POINTS

- There is no single perfect solution to understanding nature-related or 'biodiversity' impacts. Multiple approaches, including traditional ESG data points, will need to be triangulated to generate as much insight as possible.
- Here we explore geospatial ESG, one possible data solution, to aid in the generation of additional insight into the biodiversity and ecosystem impacts of commercial assets (e.g. a farm, road or factory).
- Assets are compared against observational datasets – geospatial data covering some relevant metric, such as forest loss – to give consistent insight for all assets in a given sector (e.g. palm oil).
- Results can then be aggregated from the asset level to company and then to portfolio. Or results can be generated for a given area, such as a water basin, state or country, to provide area insight for other applications, such as sovereign debt insight.
- A geospatial approach has several key advantages. First, biodiversity is highly site-specific: understanding where it is and the spatial relationship with companies' activities is vital. Second, in a data-poor environment, a geospatial approach can directly harness the largest data source relevant for nature-related insight at a global scale – satellite-derived data.
- The approach is also both data- and model-agnostic and, as a result, highly flexible to adaptation and improvement over time.
- The approach faces major barriers in delivering results for all sectors, namely a lack of asset data (defining the location and ownership of commercial assets) and supply chain data.

EXPLORING THE GEOSPATIAL SOLUTION

Any insights – metrics produced to define the ecosystem and biodiversity impact of a commercial asset – must tell us what is happening at a suitable level of reliability. As established, a highly granular understanding of impact often requires long-term in-situ ground studies – which are not a practical or viable solution for FIs, which need insight at global scale, consistently, week on week. Instead, we urgently need robust ex-situ solutions which can be scaled globally and produced regularly and which are flexible enough in design to allow future iteration and improvement to enable more granular insight.

Fortunately, over the last decade progress has been made in growing fields of research, exploring the use of emerging technologies (e.g. AI, Satellite Remote Sensing (SRS) and ecological modelling) to develop solutions to tackle some of humanity’s most pressing problems.⁷⁶ Against this backdrop of progress, here we consider the value of these developments, via a geospatial data approach, for improved ecosystem and biodiversity impact insight.

WHAT IS THE GEOSPATIAL APPROACH?

The basic approach is simple enough: the precise location of a commercial asset is defined and then assessed or modelled with ‘observational datasets’, primarily other geospatial datasets, to provide ESG-relevant insight. This approach, termed geospatial ESG, can be used to generate insight into social, governance or environmental topics, such as the impact of droughts on employment. Here we focus on ‘E’, and specifically ecosystem and biodiversity impact insights. Two terms are key;

- **Asset data** – Datasets, often grouped by sector, defining the location and ideally the property boundaries (as a point, linear or polygon feature) of commercial assets (e.g. a factory, farm, mine, road, etc.), their ownership, and frequently key attributes of the asset class (e.g. type of power plant, production, date of construction, etc.).
- **Observational data** – Any data applied, often geospatially defined, to generate insight into assets. For ecosystem impact, variables such as methane emissions, habitat clearance, biomass loss, deforestation, habitat fragmentation, endangered species proximity, habitat connectivity, etc.

The basic concept of the geospatial approach is illustrated below (Figure 16):

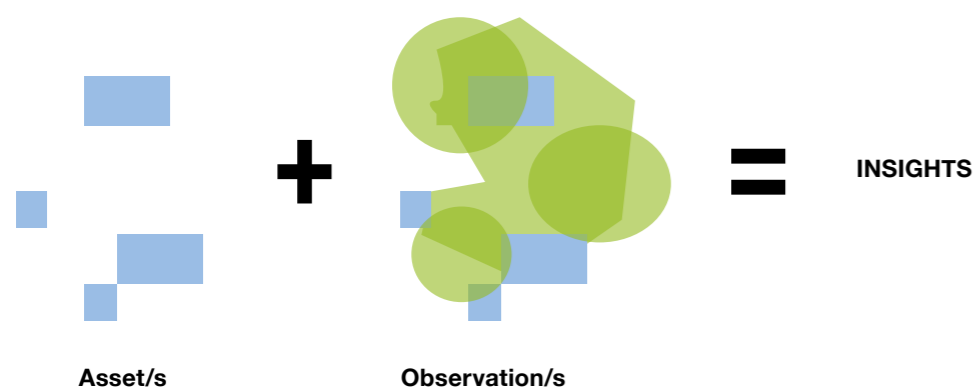


Figure 16 – Diagram illustrating the basics of a geospatial ESG approach. Asset data, defining the location of a company’s properties (assets), is compared against one or multiple observational datasets to provide insight. More complex models can be built, but the first step is the accurate location and ownership of assets, enabling any assessment.

AGGREGATING RESULTS

A company is the sum of its parts. Each asset, each operation of a company, has a differing ecosystem and biodiversity impact; an increasingly established way to understand impact is to assess each part of the company in turn.

A geospatial approach allows us to do this, to look at each asset in turn, including all supply chain assets.⁷⁷ These results can then be aggregated,⁷⁸ linking values by ownership, to parent company, then to portfolio as required. The same asset and observational data can be applied to provide regional or national results, to help provide consistent cumulative impact insight, and for other financial applications, such as sovereign debt insight (Figure 17).

TIER 0 - COUNTRY LEVEL

Summed or aggregated scores for countries, based on Tier 3 and 4 data.

TIER 1 - PORTFOLIO LEVEL

Summed or aggregated scores for countries, based on Tier 2 company scores.

TIER 2 - PARENT/COMPANY LEVEL

Summed or aggregated scores for parents companies, based on Tier 3 and 4 results.

TIER 3 - ASSET LEVEL

Assessment of the asset - GIS overlaps, remote sensing, plus Tier 4.

TIER 4 - SUB-ASSET LEVEL DATA

Assessment within the asset - IOT, smart meters, traditional ESG reporting etc.

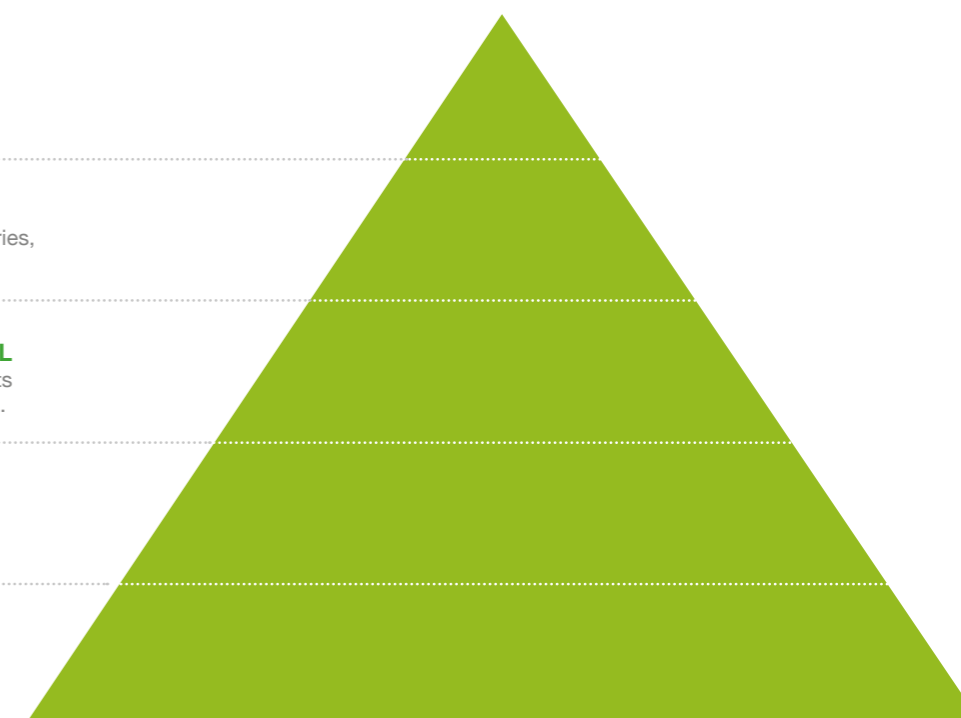


Figure 17 – Diagram adapted from WWF, World Bank and Global Canopy, 2022⁷⁹ – a hierarchy linking sub-asset assessments to corporate performance to the portfolio to national scales. Illustrating a simple method to provide methodically consistent results, at differing scales, relevant for different financial applications and audiences.

This ability to aggregate results consistently is important as FIs need insight at differing scales. For project finance, single asset screening is important, while corporates’ and portfolios’ results are need for investment and national scale insights for sovereign debt. Data consistency, where the same observational data can be applied and summed at different scales, is helpful as it means that different metrics can align. Of course, where suitable and useful localized, or ecosystem-specific, industry-specific observational datasets can be applied. And differing weightings can be applied throughout to prioritize different impacts (e.g. deforestation within supply chains).

Next, we’ll look in detail at the two major components that make up the geospatial ESG approach: asset and observational data.

ASSET DATA

Asset data is currently only available for half a dozen sectors (e.g. mining, oil and gas, power plants, cement, steel facilities). It often only exists commercially where there has been a historic application for such data.

To fill data gaps, or place data into the open sphere, we've seen a range of open data initiatives work towards generating asset datasets. Global Energy Observatory, WRI, Google and others developed a Global Power Plant Database; more recently, Descartes Labs, Oxford University developed one on solar facilities. Some datasets are generated manually; others have been developed using remote sensing, identifying assets from their specific profile (e.g. solar panels' reflective values). The table below (Figure 18) illustrates both open and commercial examples:

Asset Dataset	Developer/s	Open / Propriety	Est. No. of Asset	Est. No. of Assets with Operator / Ownership	No. of Attributes	Date of last Update	Next Update
Global Power Plant Database ⁹⁰	Global Energy Observatory/ Google/KTH Royal Institute of Technology in Stockholm/ Enipedia/WRI	Open (CC BY 4.0)	34,936	20,868	36	June 2021	'Not Foreseeable'
Solar Farms	Global Energy Monitor	Open (CC BY-NC-SA 4.0)	9,331	8,492	27	May 2022	Live
Oil and Gas Extraction ⁶¹			5,182	4847	22	January 2022	Live
Coal Mines			3,012	3,007	52	March 2022	Live
Coal Power Plants			13,412	13,412	37	January 2022	Live
Global Inventory of Utility-Scale Solar Energy Installations ⁹²	University of Oxford/ Descartes Lab/WRI	Open (CC BY 4.0)	68,661 ⁸³	0	50	Published Oct 27, 2021 – providing coverage from June 2016 to October 2018.	Irregular
Palm Oil Concessions	WRI	Open (CC BY 4.0)	2,233	2,106	21	December 2021	Irregular
Cement Facilities	University of Oxford	Unknown	3,117	Unknown	18	Unknown	Unknown
Steel and Iron		Unknown	1,598	Unknown	19	Unknown	Unknown
Power Plants	S&P Global	Propriety	120,000+	120,000+	40+	Current	Live
Solar Installations		Propriety	20,000+	20,000+	40+	Current	Live
Mining Projects		Propriety	35,000+	35,000+	30+	Current	Live
Oil and Gas Wells ⁸⁴	Enverus	Propriety	550,000+	550,000+	80+	Current	Live
Oil and Gas Field	Global Data	Propriety	30,000+	30,000+	Unknown	Current	Live
Mining Projects		Propriety	30,000+	30,000+	Unknown	Current	Live
Power Plants		Propriety	160,000+	160,000+	Unknown	Current	Live
Aviation (Commercial aircraft)	Cirium	Propriety	110,000+	Unknown	Unknown	Unknown	Unknown
Cement Facilities	Global Cement Directory	Propriety	2,800+	2,800+	Unknown	Annual	Annual / 2023

Figure 18 – A table providing examples of current open and commercial asset datasets. Values reported are estimates and may contain errors. Datasets sourced may not be the most recent available.

For the geospatial approach to function, its needs asset data. On Page 99, we explore and discuss practical means to generate this data at scale (millions of assets) for 95% of listed and unlisted companies' assets.

ASSET PROPERTY BOUNDARIES

To provide robust geospatial ESG insight, it is preferable that asset datasets do not define location by a single point location but by polygons, accurately geolocating the property boundaries of each asset within the asset dataset. As the area assessed directly determines the results generated, an incorrect area is likely to bias outputs. Correct delineation allows both an estimate of the holder's responsibility (e.g. extent of environmental assets under ownership) and their accountability (e.g. extent of environmental assets cleared or impacted under ownership). These data are particularly needed for sectors with large land holdings, whose property boundaries are frequently unclear (e.g. mining and agriculture); they are arguably less essential for some sectors, such as real estate, where highly accurate estimates of property boundaries can more easily be discerned from satellite imagery.

It is of course possible, lacking property boundaries, to use point location data and apply a buffer (e.g. a 1km circle around the asset) or create estimated areas of operation, where for example, Maus et al., 2020 successfully estimated the area of operation of 6,021 mines globally from satellite imagery (Figure 19).

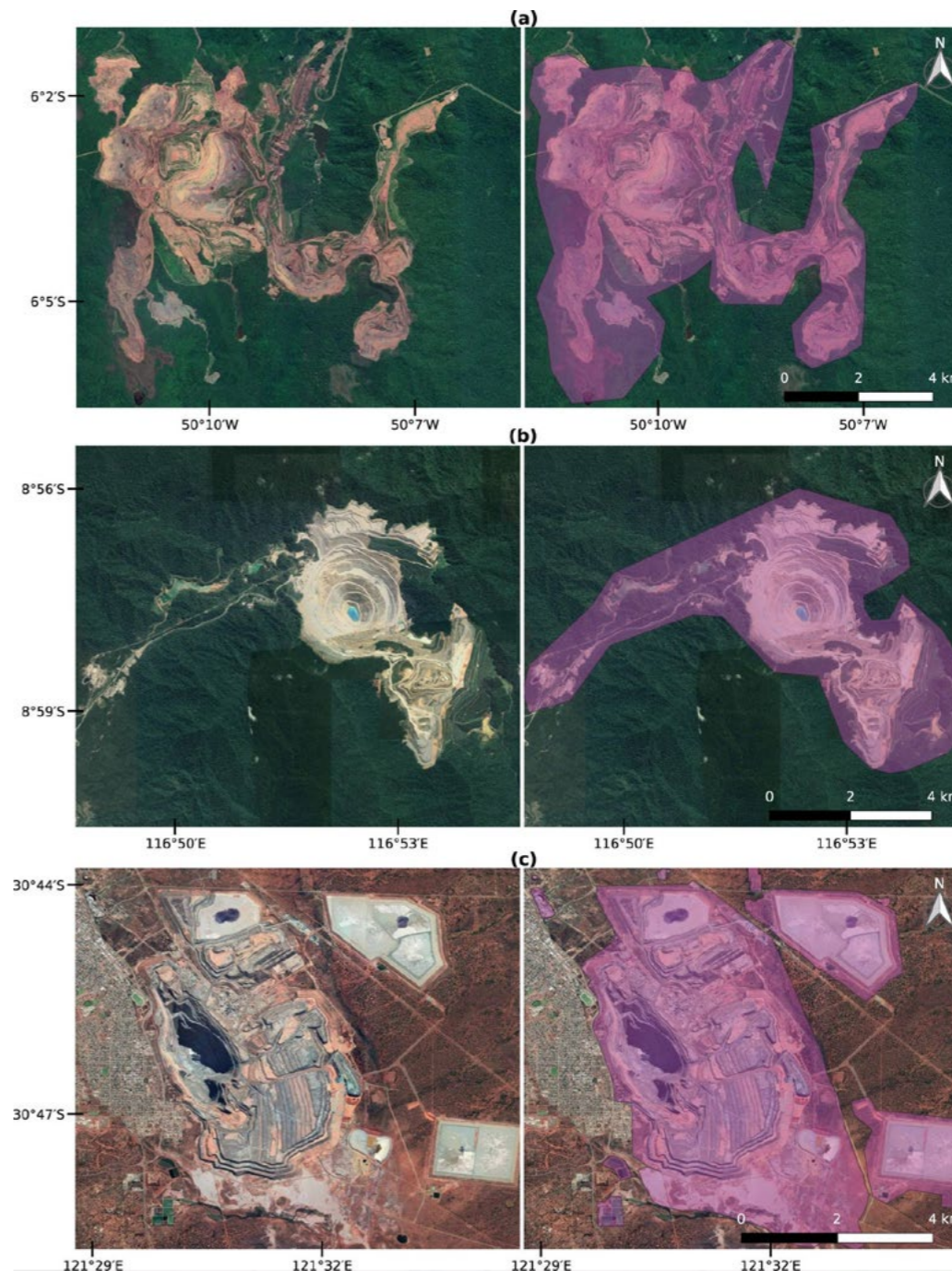


Figure 19 – From Maus et al., 2020⁸⁵ – An example of how satellite imagery has been applied to estimate the extent of mining operations. While useful, it highlights the need within geospatial ESG for the true property boundaries to be established for accurate, consistent assessments of ecosystem and biodiversity impact within an asset's directly owned and managed land.

OTHER ASSET DATASET CONSIDERATIONS

‘SUPPLY CHAIN’ ASSETS

It should be briefly noted that there is no distinction between a ‘supply chain’ asset and a directly owned asset within asset datasets. The rationale for this is simple: everything, depending on the perspective, is an asset. What might be a ‘supply asset’ in one company’s supply chain is simply an asset for its own company. If we geolocate every asset on Earth,⁸⁶ we can assess every asset uniquely and provide insight. That insight can later be aggregated and adjusted – linking assets’ results together within a specific supply chain to give supply chain ‘scores’ or insight. And of course, we can keep track of the fact that these assets are, within this use case, ‘supply assets’ and not directly held assets within that company/portfolio.

SUB-ASSET

Within certain asset classes there are physical components which can be of special interest for geospatial ESG insight. An example of this is tailing dams: dams used by the mining sector to retain water and the chemical by-products of mining, refining or smelting. These large bodies of water and hazardous waste are normally located within the mining property. The Dam Monitoring from SATellites (DAMSAT) initiative⁸⁷ uses satellite data (ex-situ metrics) to monitor these assets, the failure of which can present serious environmental, social and economic consequences. Such sub-asset insights can of course be linked into the geospatial ESG insights.

COMPANY TREES (ENTITY MATCHING)

It is important that subsidiary companies are correctly assigned to the correct parent company for insight aggregation (See Page 43). For technical ease and to lower the potential for error, this linkage should be included within the asset datasets themselves, where the attributes should include the subsidiary name and unique identifiers of the direct owner, any partial ownership, royalty holders, etc., and the parent company name, and its identifiers (e.g. tickers, LEI, GLN). Such identifiers are important, and asset data development efforts should align to ongoing efforts to support entity matching. Finally, complications in ownership, such as shared ownership, where multiple parties may own a percentage of an asset, pose little technical difficulty, but standards must be established to ensure results are consistently aggregated and reported. At the simplest level, the assets’ variables can be assigned to all holders, with no differentiation as to % of ownership (e.g. dividing impact by % of ownership).

OBSERVATIONAL DATA AND METRICS

Observational data are the data applied onto asset data to provide insight. The analysis, measurement, conversion, weighting and normalization of the observational data, alone or with other datasets, produces metrics. For example, the observational dataset of a geospatial layer defining global forest loss, applied against a palm oil sector asset dataset, creates the metric, ‘12-month deforestation risk (per km²)’ for palm oil plantations. Non-geospatial data can be combined within the approach, as can multiple datasets, data triangulation, machine learning, etc., to produce more refined and complex metrics (See Page 55).

It is difficult to discuss observational data without discussing metrics, as understandably interest is immediately placed on gaining insight from observational data. However, it is vital to make the distinction, as often observational datasets are frequently used as proxy measurements inferring relationships. And one observational dataset can be applied in slightly differing ways to produce dozens of metrics. For example, the observational datasets ‘protected areas’ and ‘national boundaries’ are often applied as the metric ‘national protected area extent %’, inferring better national biodiversity and ecosystem performance from larger percentages. But they are also applied to produce metrics defining the extent of land under differing protected area management categories – protected within each municipality, state or water basin, etc.

Currently across the metric space, confusion reigns – a vast array of nature-related metrics now exist, attempting to provide insights across ‘biodiversity’-related topics, such as dependencies, impacts, risk and opportunities. Indeed, TNFD reported that there are over 3,000 different nature-related metrics in use today,⁸⁸ noting that the lack of standardization of nature-related metrics is a limiting factor on FIs’ understanding and reporting. Even within emerging standards, it isn’t yet clear on what the metrics should be applied. The draft ESRS⁸⁹ under its application guidance states, ‘Performance measures

on Biodiversity and ecosystems are currently the object of many ongoing collective work at the time of the drafting of this Standard. That is why the disclosure requirements proposed in this [Draft] Standard are mostly principles-based, so as to clarify the categories of performance measures expected, as well as laying out the features of quality biodiversity and ecosystems-related measures rather than proposing specific measures per se.’

For those corporates and FIs working to meet these emerging standards. this could be frustrating – and likely to create dissatisfaction and inconsistency in the results reported. **And yet this position is fully understandable, as there is no current perfect solution, or even widely used or accredited approach.** Here we look at geospatial ex-situ metrics for supporting nature-related insight.

GEOSPATIAL METRICS

Many of the 3,000 metrics in use today for nature-related insight are geospatially based, often either direct products of Satellite Remote Sensing (SRS), derived products or aggerated products (e.g. indices) formed from one or multiple geospatial datasets and in some cases non-spatial data.

It is useful to make a distinction between the different types of data used. Broadly speaking they can be divided into two groups. **Vector** datasets are often man-made delineations: country boundaries, protected areas, indigenous areas, key biodiversity areas, marine protected areas, important marine mammal areas, estimated species ranges, etc. **Raster** files, grids of pixels often used to represent continuous phenomena or variables, are equal-area squares with a given specific value, frequently generated from SRS data (e.g. satellite imagery) and 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.

Here, with input from Maxar we explore the current data landscape and potential future developments.

CURRENT SITUATION – COMMON ISSUES WITH GEOSPATIAL OBSERVATIONAL DATA

There is much to say on the various common data issues with geospatial observational datasets.⁹⁰ For brevity, the common issues faced are:

Temporal Consistency	Often datasets do not update frequently enough to support timely ESG insight or to monitor trends, often updating once per annum or not at all.
Spatial Resolution	Datasets (particularly those in the open data space) can have a low spatial resolution. This for some applications can lack the required detail to detect variables.
Accuracy	Often raster observational datasets are generated from 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’.
Data Interdependencies	Due to the challenges involved in creating global observational datasets and the narrow pool of robust global layers, some observational datasets may draw from the same source data.
Relevancy	Due to the technical difficulty in measuring certain variables, some topics, including ecosystem condition, are not well documented within the observational data portfolio.



Lesser Flamingo, Lake Nakuru National Park, Kenya
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IMPLICATIONS

As a result of the current observational data landscape, where often there is a lack of consistent data over time and a lack of measurements in key areas – we frequently see the application of low temporal resolution data or the next best available proxies. The extent to which these proxy metrics can holistically account for specific impacts at the site level is often unclear. Consequently, unpicking how well or even what exactly these metrics capture and define, in terms of real-world biodiversity and ecosystem impact, is often challenging. For example, an asset’s proximity to areas of low human footprint, to protected areas or to endangered species has an unclear relationship to actual impact. Observational data can also be applied incorrectly. An increasingly common problem in emerging geospatial data products, is ‘**temporal false negatives**’ – this occurs when the observational dataset applied predates the asset under observation. For example, a palm oil plantation was developed, clearing primary rainforest in 2007, but the observational ground carbon data applied is from 2020 onwards and consequently reports 0 km² for the asset, as it is measuring the already cleared site.

WHAT OBSERVATIONAL DATA SHOULD BE USED?

Geospatial observational datasets are highly diverse; however, there are common traits which on average make them more useful within geospatial ESG applications, namely:

- **High frequency** – datasets which update with a high frequency (e.g. daily, weekly) are often more able to capture impact and define trends over time.
- **High and Moderate spatial resolution** – metrics needs to be based on a combination of data at resolution/s sensitive enough to able to detect change within the measured variable; often nature-related variables require higher resolution imagery (≤15m) to detect subtle impacts (e.g. clearance of small blocks of habitat)
- **Accuracy** – observational datasets need two forms of accuracy: values need to achieve a level of accuracy (e.g. are correct), but also values need to determine variables at the required level of distinction (e.g. ‘pine forest’ and not just ‘forest’).
- **Relevancy** – metrics must capture a specific variable (i.e. extent of forest loss). Those which are more closely aligned to the desired measurement variable (i.e. habitat loss) are more likely to be of greater utility.
- **Consistency** – data must be consistently produced if it is to be comparable with prior data points and users can trust that it will be continually available.
- **Wide Application** – Ideally (but it is not always feasible), outputs should be applicable to a wide range of ecosystems (although there is the potential for ecosystem/sector-specific metrics).

Observational data, with progress in satellite technology, machine learning etc., will change over time, as will geospatial ESG methods and models. The perspective at which different users will wish to view ecosystem and biodiversity impact will also vary from actor to actor, as will FIs’ requirements and exposures. As a result, no observational dataset or derived metric can be considered the ‘right’ or permanent solution. However, while at this time there is no widely agreed set of metrics for ex-situ ‘ecosystem and biodiversity’ insight, as the field evolves, we expect iteration, testing, review and benchmarking to occur and that actors are likely to gravitate organically to the most proven observational data and metrics for specific use cases.

To give an illustration of what is available currently likely to be available within the immediate future, we outline the types of observational datasets and metrics that could be generated to provide insight:

OBSERVATIONAL DATA / METRICS

To give a sense of the status of SRS science and its relevance to geospatial ESG, here, structured into the approach applied within this document, we provide a few current examples capable, or potentially capable, of providing insights for 1) environmental context, 2) ecosystem condition, 3) direct impact and 4) indirect impact.

It is important to note that the data produced by these approaches can be used alone or applied to update or refine existing vector datasets, such as datasets defining biomes, ecoregions, water basins, etc. Or it can be used in combination with other vector datasets (e.g. protected areas, IP lands) to produce additional metrics (e.g. forest loss within protected areas).

	Observational Data	Metric	What it Measures	Frequency	Current Examples
Environmental Context	Satellite imagery based land cover classification	Biome	Large unit of land or water (also vegetation) adapted to a specific climate	Yearly	Fonseca, L.M.G., Körting, T.S., Bendini, H. do N., Girolamo-Neto, C.D., Neves, A.K., Soares, A.R., Taquary, E.C. and Mareto, R.V. (2021). Pattern Recognition and Remote Sensing techniques applied to Land Use and Land Cover mapping in the Brazilian Savannah. <i>Pattern Recognition Letters</i> , 148, pp.54–60.
	Satellite imagery based land cover classification	Ecoregion	Large unit of land or water containing a geographically distinct collection of species, natural vegetation, and environmental conditions	Monthly	Pötzschnner, F., Baumann, M., Gasparri, N.I., Conti, G., Loto, D., Piquer-Rodríguez, M. and Kuemmerle, T. (2022). Ecoregion-wide, multi-sensor biomass mapping highlights a major underestimation of dry forests carbon stocks. <i>Remote Sensing of Environment</i> , 269, p.112849. doi:10.1016/j.rse.2021.112849.
	Satellite imagery based water classification algorithms; Elevation datasets	Water basin	Surface water extent, drainage basin extent	As often as new imagery becomes available	Duan, W., Maskey, S., Chaffe, P.L.B., Luo, P., He, B., Wu, Y. and Hou, J. (2021). Recent Advancement in Remote Sensing Technology for Hydrology Analysis and Water Resources Management. <i>Remote Sensing</i> , 13(6), p.1097. doi:10.3390/rs13061097.
	DSM, DTM, DEM, Point Cloud	Elevation	Slope, aspect, height of bare earth, vegetation, and man-made features	Bare earth elevation models change infrequently- less than yearly. Changes in man-made features can be detected more frequently.	Rukhovich, D.I., Koroleva, P.V., Rukhovich, D.D. and Rukhovich, A.D. (2022). Recognition of the Bare Soil Using Deep Machine Learning Methods to Create Maps of Arable Soil Degradation Based on the Analysis of Multi-Temporal Remote Sensing Data. <i>Remote Sensing</i> , 14(9), p.2224. doi:10.3390/rs14092224.
	Satellite imagery based land cover classification	Land cover	Classification of the physical material on the surface of the Earth	Post event; monthly-yearly.	Sarif, M.O. and Gupta, R.D. (2021). Spatiotemporal mapping of Land Use/Land Cover dynamics using Remote Sensing and GIS approach: A case study of Prayagraj City, India (1988–2018). <i>Environment, Development and Sustainability</i> , 24, 888–920. doi:10.1007/s10668-021-01475-0.
	Satellite imagery based land cover classification	Forest cover	Classification of the health and extent of the forest land class	Post event; monthly-yearly.	Sarif, M.O. and Gupta, R.D. (2021). Spatiotemporal mapping of Land Use/Land Cover dynamics using Remote Sensing and GIS approach: A case study of Prayagraj City, India (1988–2018). <i>Environment, Development and Sustainability</i> , 24, 888–920. doi:10.1007/s10668-021-01475-0.
	Satellite imagery based land cover classification	Sub-metrics considering key forest types of Primary / Secondary Forest / Forestry Plantation / Palm Oil	Classification of the health and extent of the forest land class and its sub-classes.	Post event; monthly-yearly.	Sarif, M.O. and Gupta, R.D. (2021). Spatiotemporal mapping of Land Use/Land Cover dynamics using Remote Sensing and GIS approach: A case study of Prayagraj City, India (1988–2018). <i>Environment, Development and Sustainability</i> , 24, 888–920. doi:10.1007/s10668-021-01475-0.
	Satellite imagery based land cover classification	Extent of Intact Forest Landscapes and other conservation areas	Classification of the health and extent of the forest land class	Post event; monthly-yearly.	Filewod, B. and Kant, S. (2021). Identifying economically relevant forest types from global satellite data. <i>Forest Policy and Economics</i> , 127, p.102452.
	Satellite imagery based land cover classification	Mangrove forest extent	Classification of the health and extent of the mangrove forest land class	Post event; monthly-yearly.	Lee, C.K.F., Duncan, C., Nicholson, E., Fatoyinbo, T.E., Lagomasino, D., Thomas, N., Worthington, T.A. and Murray, N.J. (2021). Mapping the Extent of Mangrove Ecosystem Degradation by Integrating an Ecological Conceptual Model with Satellite Data. <i>Remote Sensing</i> , [online] 13(11), p.2047. doi:10.3390/rs13112047.
	Satellite imagery based land cover classification	Grassland extent	Classification of the physical material on the surface of the Earth	Post event; monthly-yearly.	Khazieva, E., Verburg, P.H. and Pazúr, R. (2022). Grassland degradation by shrub encroachment: Mapping patterns and drivers of encroachment in Kyrgyzstan. <i>Journal of Arid Environments</i> , 207, p.104849.
Satellite imagery based land cover classification	Species insights (i.e. total % of species range, abundance, richness, etc.)	Vegetation species identification and biodiversity/ spectral diversity relationships	Post event; monthly-yearly.	Rossi, C., Kneubühler, M., Schütz, M., Schaepman, M.E., Haller, R.M. and Risch, A.C. (2021). Spatial resolution, spectral metrics and biomass are key aspects in estimating plant species richness from spectral diversity in species-rich grasslands. <i>Remote Sensing in Ecology and Conservation</i> , 8(3), 297–314. doi:10.1002/rse2.244.	

	Observational Data	Metric	What it Measures	Frequency	Current Examples
Ecosystem Condition	Satellite imagery based remote sensing algorithm	Leaf area index	Ratio of leaf area to per unit ground surface used as a stress indicator for vegetation canopies	Post event; weekly, monthly, yearly	Hirigoyen, A., Acosta, C., Ariza, A., Vero-Martinez, M.A., Rachid, C., Franco, J. and Navara-Cerrillo, R. (2022). A machine learning approach to model leaf area index in Eucalyptus plantations using high-resolution satellite imagery and airborne laser scanner data. <i>Annals of Forest Research</i> , 64(2), pp.165–183. doi:10.15287/afr.2021.2073.
	Satellite imagery based remote sensing algorithm	Foliar nitrogen content	Relative nitrogen content in vegetation	Post event; weekly, monthly, yearly	Wu, H., Levin, N., Seabrook, L., Moore, B. and McAlpine, C. (2019). Mapping Foliar Nutrition Using WorldView-3 and WorldView-2 to Assess Koala Habitat Suitability. <i>Remote Sensing</i> , 11(3), p.215. doi:10.3390/rs11030215.
	Multiview photogrammetry	Vegetation height	Vegetation height can be calculated using satellite imagery from multiple look angles	Pre-event, post event, yearly	Gazzea, M., Aalhus, S., Kristensen, L. M., Ozguven, E. E. and Arghandeh, R. (2021). Automated 3D vegetation detection along power lines using monocular satellite imagery and deep learning. <i>2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS</i> , 3721–3724.
	Satellite imagery based land cover classification	Habitat structure	Classification of the type and distribution of vegetation	Post event; weekly, monthly, yearly	Merrington, A.T., Milodowski, D.T. and Williams, M. (2021). Optimising remotely sensed land cover classification for habitat mapping in complex Scottish upland landscapes. <i>Space, Satellites, and Sustainability II</i> , 11888, p.118880G. doi:10.1117/12.2600869.
	Satellite imagery based remote sensing algorithm	Fraction of vegetation cover	A ratio (usually percentage) of total vegetated area to the total study area	Post event; weekly, monthly, yearly	Ma, X., Lu, L., Ding, J., Zhang, F. and He, B. (2021). Estimating Fractional Vegetation Cover of Row Crops from High Spatial Resolution Image. <i>Remote Sensing</i> , 13(19), p.3874. doi:10.3390/rs13193874.
	Satellite imagery based remote sensing algorithm	Chlorophyll content	A key indicator of leaf greenness and nutrient deficiencies	Post event; weekly, monthly, yearly	Zhang, H., Li, J., Liu, Q., Lin, S., Huete, A., Liu, L., Croft, H., Clevers, J.G.P.W., Zeng, Y., Wang, X., Gu, C., Zhang, Z., Zhao, J., Dong, Y., Mumtaz, F. and Yu, W. (2022). A novel red-edge spectral index for retrieving the leaf chlorophyll content. <i>Methods in Ecology and Evolution</i> . 00, 1-17. doi:10.1111/2041-210x.13994.
	Satellite imagery time-series based deep learning models	Land surface green-up	Onset of seasonal vegetation growth	Seasonally	Lake, T.A., Briscoe Runquist, R.D. and Moeller, D.A. (2022). Deep learning detects invasive plant species across complex landscapes using Worldview-2 and Planetscope satellite imagery. <i>Remote Sensing in Ecology and Conservation</i> . doi:10.1002/rse2.288.
	Satellite imagery time-series based deep learning models	Land surface senescence	Conclusion of seasonal vegetation growth	Seasonally	Lake, T.A., Briscoe Runquist, R.D. and Moeller, D.A. (2022). Deep learning detects invasive plant species across complex landscapes using Worldview-2 and Planetscope satellite imagery. <i>Remote Sensing in Ecology and Conservation</i> . doi:10.1002/rse2.288.
	Satellite imagery time-series based remote sensing classifications and algorithms	Above-ground biomass (carbon cycle)	Mass of living vegetation above the soil surface	Post event; weekly, monthly, yearly	Zhu, Y., Liu, K., Liu, L., Myint, S.W., Wang, S., Cao, J. and Wu, Z. (2020). Estimating and Mapping Mangrove Biomass Dynamic Change Using WorldView-2 Images and Digital Surface Models. <i>IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing</i> , 13, pp.2123–2134. doi:10.1109/jstars.2020.2989500.
	Satellite imagery based remote sensing algorithms	Leaf dry matter content	Remote sensing index (ratio) of leaf dry matter to saturated fresh mass; used to indicate vegetation growing conditions	Post event; weekly, monthly, yearly	Zhang, Z., Tang, B.-H. and Li, Z.-L. (2018). Retrieval of leaf water content from remotely sensed data using a vegetation index model constructed with shortwave infrared reflectances. <i>International Journal of Remote Sensing</i> , 40(5-6), pp.2313–2323. doi:10.1080/01431161.2018.1471553.
Satellite imagery based remote sensing algorithms	Ecosystem soil moisture	Measure of soil moisture content; an indicator of the health or stress of land surface ecosystems	Post event; weekly, monthly, yearly	Son Le, M. and Liou, Y.-A. (2021). Temperature-soil moisture dryness index for remote sensing of surface soil moisture assessment. <i>IEEE Geoscience and Remote Sensing Letters</i> , 19, 1–5	

	Observational Data	Metric	What it Measures	Frequency	Current Examples
Direct Impact	Satellite imagery based land cover classification	Land cover change / Habitat loss	Classification of the health and extent of the designated land cover class and its sub-classes.	Post event; monthly-yearly.	Smith, K.E.L., Terrano, J.F., Pitchford, J.L. and Archer, M.J. (2021). Coastal Wetland Shoreline Change Monitoring: A Comparison of Shorelines from High-Resolution WorldView Satellite Imagery, Aerial Imagery, and Field Surveys. <i>Remote Sensing</i> , 13(15), p.3030. doi:10.3390/rs13153030.
	Satellite imagery based remote sensing algorithms	Forest loss	Forest species identification and biodiversity/spectral diversity relationships	Post event; monthly-yearly.	Jackson, C.M. and Adam, E. (2021). Machine Learning Classification of Endangered Tree Species in a Tropical Submontane Forest Using WorldView-2 Multispectral Satellite Imagery and Imbalanced Dataset. <i>Remote Sensing</i> , 13(24), p.4970. doi:10.3390/rs13244970.
	Satellite imagery based remote sensing algorithm	Forest gain	Forest species identification and biodiversity/spectral diversity relationships	Post event; monthly-yearly.	Kamal, M., Sidik, F., Prananda, A.R.A. and Mahardhika, S.A. (2021). Mapping Leaf Area Index of restored mangroves using WorldView-2 imagery in Perancak Estuary, Bali, Indonesia. <i>Remote Sensing Applications: Society and Environment</i> , 23, p.100567.
	Satellite imagery based land cover classification	Sub-metrics considering key forest types of Primary / Secondary Forest / Forestry Plantation / Palm Oil	Classification of the health and extent of the designated land cover class and its sub-classes in secondary forests	Post event; monthly-yearly.	Zhao, Y., Ma, Y., Quackenbush, L.J. and Zhen, Z. (2022). Estimation of Individual Tree Biomass in Natural Secondary Forests Based on ALS Data and WorldView-3 Imagery. <i>Remote Sensing</i> , 14(2), p.271. doi:10.3390/rs14020271.
	Satellite imagery based remote sensing algorithms	Soil exposure	Soil quality assessment and identification / spectral diversity relationships	Post event; monthly-yearly.	Galle, N.J., Brinton, W., Vos, R., Basu, B., Duarte, F., Collier, M., Ratti, C. and Pilla, F. (2021). Correlation of WorldView-3 spectral vegetation indices and soil health indicators of individual urban trees with exceptions to topsoil disturbance. <i>City and Environment Interactions</i> , 11, p.100068. doi:10.1016/j.cacint.2021.100068.
	Satellite imagery based remote sensing algorithms	Fire intensity and burn extent	Fire extent assessment and identification / spectral diversity relationships	Post event; monthly-yearly.	Fernández-Guisuraga, J.M., Verrelst, J., Calvo, L. and Suárez-Seoane, S. (2021). Hybrid inversion of radiative transfer models based on high spatial resolution satellite reflectance data improves fractional vegetation cover retrieval in heterogeneous ecological systems after fire. <i>Remote Sensing of Environment</i> , 255, p.112304. doi:10.1016/j.rse.2021.112304.
	Satellite imagery based remote sensing algorithms	Landslide impact	Landslide conditioning factor assessment and identification	Post event; monthly-yearly.	Singh, P., Sharma, A., Sur, U. and Rai, P.K. (2020). Comparative landslide susceptibility assessment using statistical information value and index of entropy model in Bhanupali-Beri region, Himachal Pradesh, India. <i>Environment, Development and Sustainability</i> , 23(4), pp.5233–5250. doi:10.1007/s10668-020-00811-0.

	Observational Data	Metric	What it Measures	Frequency	Current Examples
Indirect Impacts (4-Sector Specific Metrics)		Interannual variability	Year over year changes in health and extent of various vegetation species	Seasonally, yearly	Li, Z., Sun, W., Chen, H., Xue, B., Yu, J. and Tian, Z. (2021). Interannual and Seasonal Variations of Hydrological Connectivity in a Large Shallow Wetland of North China Estimated from Landsat 8 Images. <i>Remote Sensing</i> , 13(6), p.1214. doi:10.3390/rs13061214.
	Satellite imagery time-series based machine learning classification models	Seasonal variability	Seasonal changes in health and extent of various vegetation species	Seasonally, yearly	Colkesen, I., Kavzoglu, T., Atesoglu, A., Tonbul, H. and Ozturk, M.Y. (2022). Multi-seasonal evaluation of hybrid poplar (<i>P. Deltoides</i>) plantations using Worldview-3 imagery and State-Of-The-Art ensemble learning algorithms. <i>Advances in Space Research</i> .
	Satellite imagery based remote sensing algorithms	Coastal eutrophication potential	Excessive nutrient levels in coastal water bodies	Pre-event, post event, as needed	Ben Hadid, N., Goyet, C., Ben Maiz, N. and Shili, A. (2022). Long-term forecasting in a coastal ecosystem: case study of a Southern restored Mediterranean lagoon: The North Lagoon of Tunis. <i>Journal of Coastal Conservation</i> , 26(2). doi:10.1007/s11852-022-00858-3.
	SAR based machine learning models	Marine oil spill detection frequency and density	Natural and/or artificial oil seeps or spills	Post-event; as needed	de Oliveira Matias, I., Genovez, P.C., Torres, S.B., de Araújo Ponte, F.F., de Oliveira, A.J.S., de Miranda, F.P. and Avellino, G.M. (2021). Improved Classification Models to Distinguish Natural from Anthropogenic Oil Slicks in the Gulf of Mexico: Seasonality and Radarsat-2 Beam Mode Effects under a Machine Learning Approach. <i>Remote Sensing</i> , 13(22), p.4568. doi:10.3390/rs13224568.

It is important to reflect that while Satellite Remote Sensing (SRS) methods offer increasing insight, and are continuously improving, no ex-situ method can measure everything. Consequently, the huge diversity of impacts facing the natural world will never be able to be captured entirely by ex-situ approaches. Understanding, for example, resource extraction (i.e. wild fish caught, bush hunting, etc.), soil pollutants, water use, solid waste or specific species ranges will in almost all cases require in-situ (ground collected) data. As in-situ data aggregation improves over the coming years at the global scale, particularly on biodiversity, it will be possible to integrate this data into the approaches outlined in this document to improve insight.

REFLECTIONS ON METRICS

Topic Difficulty – Not all metrics are equal. From a SRS perspective, some observational datasets are simpler and easier to achieve than others. What we see within the nature-related space is a ramp of difficulty, where the easier metrics have long been achieved, and the more technically difficult, such as defining ‘landscape condition’, remain out of reach. Clarity needs to be provided not only on the confidence of a metric but on which area data gaps are present within the results.

Biome Specific Metrics – As outlined at the start of this paper, each ecosystem is unique. Consequently, to improve insight it seems likely we will see the rise of ecoregion specific metrics, where it may be possible to improve insight by spatially limiting SRS methods to a given region, allowing the tailoring of approaches to the specific characteristics of nature present. Already a number of robust biome and ecoregion maps exist, which could be used to provide spatial delineations for application of these niche methods (Page 71).

Sector Specific – Already we are seeing the rise of sector specific metrics (e.g. mining tailing dam monitoring). As time goes on it is inevitable, with improvements in SRS, more and more satellites deployed, increases in AI capabilities, etc., that we will witness the increase in niche sector specific data solutions relevant for geospatial ESG applications.

Metrics Aggregation – While the development of metrics tailored to specific biomes and sectors is to be welcomed for improved insight, it comes at a potential cost. When actors attempt to aggregate data at the parent company or portfolio level, the greater and more varied the specificity of metrics applied, the harder direct aggregation will be. It seems probable that there will be other intelligent means to aggregate data – yet it is a potential shortfall in the development of greater and greater ecosystem and sector metric specificity. On Page 82 we explore the topic of quantification and aggregation in more detail.

THE ROLE OF GEOSPATIAL ESG AS A COMPONENT OF ESG

DATA TRIANGULATION

It should be stressed that no single data solution can hope to provide all the necessary components of nature-related ESG insight. Consequently, geospatial ESG insight is not a standalone ESG data solution but one of many to be integrated with others to provide improved insight.

It is interesting to reflect differing data solutions have a different proportionate relevancy in capturing impact across industry tiers. For example, it is likely that the importance of geospatial in screening a company’s direct assets decreases towards higher tiers, and the importance of screening a company’s supply chain assets increases towards higher tiers.

This is because high tier sectors are far more likely to have their directly held assets within long-established urban areas with a lower potential for destruction of natural habitats. Primary industries have comparatively smaller supply chains, and their role is likely to be proportionately lower in overall company impact, most of which will be contained in their own direct holdings and actions. Conversely, the nature-related impact of a company’s workforce is likely to be proportionately more significant in higher tiers, where often the higher tiers have larger numbers of employees relative their spatial footprint than lower tier sectors (Figure 20).

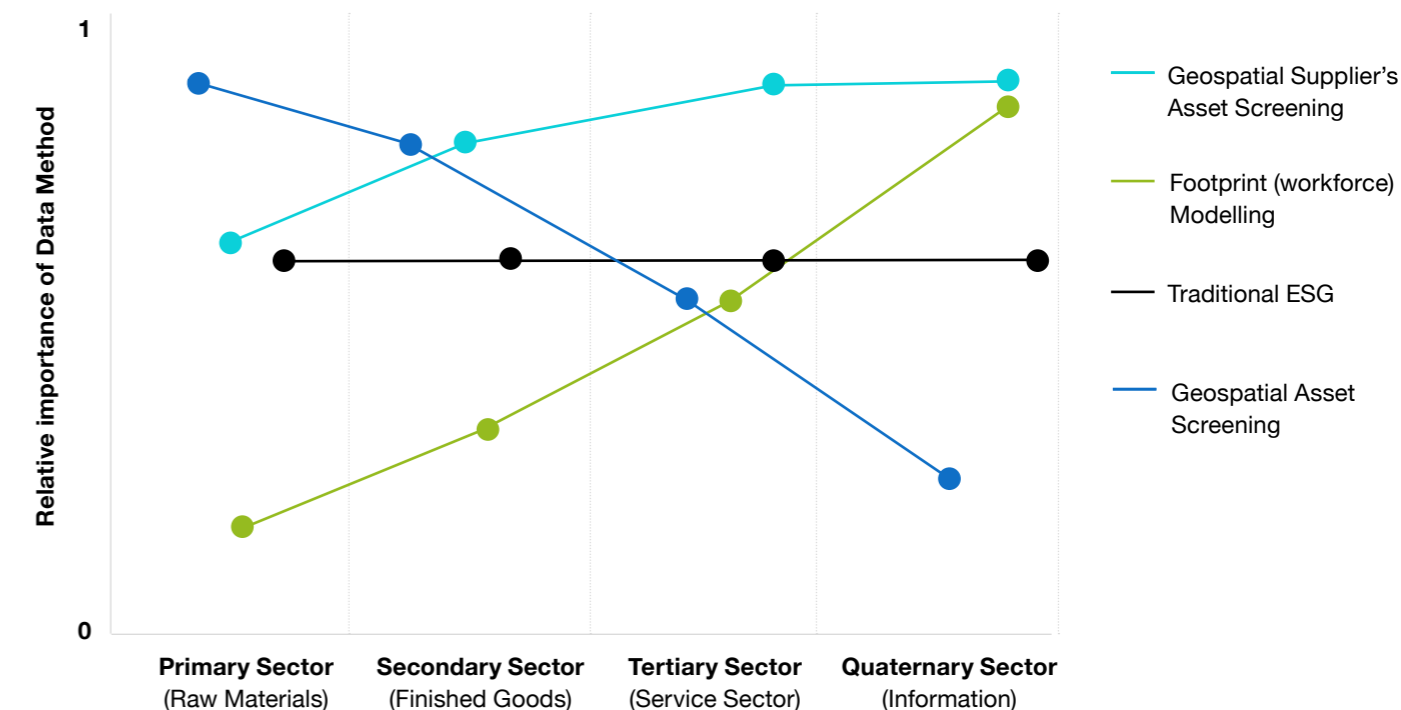


Figure 20 – Illustration of the concept that different ESG data solutions have a higher relevancy for capturing the proportional nature-related impact of differing sections of the economy.

The extent to which Figure 20 is correct is not vital. What is important is the concept that different data approaches provide insights that other approaches cannot. As geospatial insights become normalized, opportunities will arise to combine its insights with other ESG data approaches for improved holistic ESG insight. For example, one commercial provider currently uses SRS data to estimate the methane emissions of oil and gas operations within the continental United States, comparing those numbers to the companies’ officially reported emissions. Both data points, and the variance between them, provide additional ESG insight.

As an example of the value of combining differing data approaches, WWF’s Conservation Intelligence team are currently working with Carnegie Mellon University to build a library of media articles published online about impacts to conservation sites (e.g. fires, logging, poaching, heavy metal pollution, floods, etc.), geolocating articles to specific sites (See Box 4). This Natural Language Processing (NLP) driven approach is able to identify ‘entities’, such as company names, and assets and therefore has the potential to be linked to geospatial ESG insights. This provides insight on aspects impossible to detect via ex-situ SRS approaches alone, supporting additional verification, and aims to provide site level scorings for threat presence, which in turn can be used to help qualify landscape condition.

BOX 4 – DATA TRIANGULATION

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As we move forward, data triangulation will become an essential component within ESG, uniting insights from differing data solutions to fill data gaps. Here we provide an example of natural language processing (NLP) based media scraping, providing insights that could potentially be linked, via company names, asset, location or a combination, to geospatial ESG insights.

Carnegie Mellon University (CMU) worked with WWF to develop ‘NewsPanda’, a machine learning-based system which automatically detects, classifies and analyses news articles related to conservation and infrastructure. NewsPanda aims to automate processes that would otherwise be costly to do manually, such as news article collection, relevance classification and keyword extraction.

NewsPanda consists of five modules. Using names of conservation sites as search terms, the information retrieval module is able to scrape hundreds of news articles from various global and local news sites every week. The main relevance classification module then uses state-of-the-art NLP models to classify news articles along two dimensions, namely conservation relevance and infrastructure relevance. This machine learning model builds upon previous work by The Alan Turing Institute and WWF, taking into consideration certain features such as sentiment analysis polarities and topic value vectors.

Training the model involved using active learning techniques as well as ways to perform noisy label correction.⁹¹ Afterwards, in the article postprocessing module, NewsPanda extracts crucial information such as keywords and related named entities, such as specific location names, people and organizations. This is helpful in identifying common links between developments across different locations and across different points in time, helping to provide key insights to local WWF offices and field teams, as well as other parties interested in monitoring developments in conservation and infrastructure.

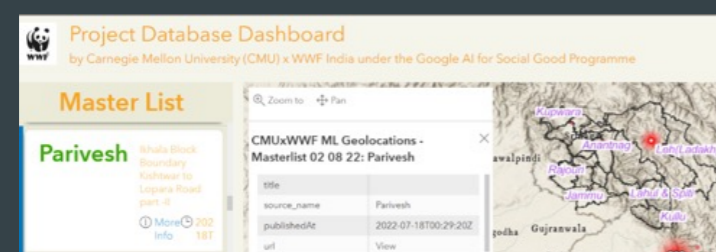


Figure 21 – The GIS dashboard by WWF India, where each relevant article is shown on the map with its corresponding key details. The highlighted red areas indicate clusters of articles found by the NewsPanda pipeline.

After generating these insights, a visualization module delivers these extracted articles and relevant locations to be consumed by the WWF staff. One such example is the GIS dashboard developed by WWF India (Figure 21). Every week, the WWF India team receives a list of news articles predicted as relevant, together with the corresponding keywords, named entities and geospatial coordinates. These relevant areas are then plotted on a dashboard, which will make it easier for field teams to explore and navigate. Furthermore, selected outputs from NewsPanda are also available to the public through a social media module on Twitter, called WildlifeNewsIndia. There are plans to extend the deployment, and work is currently being done to incorporate a broader collection of languages beyond English.

By building a global library of news articles about developments occurring within key conservation sites, NewsPanda provides a highly useful resource for conservationists but also potentially for ESG applications, where entity names (e.g. company names) could potentially be extracted and linked, and triangulated with other ESG data points.

ADVANTAGES OF A GEOSPATIAL APPROACH

The geospatial approach faces challenges, as do all methods attempting to tackle such a complex topic, but arguably the approach has several advantages:

- **Biodiversity** – The ‘biodiversity’ around you, in gardens, hedges, blocks of native habitat, are hyper-localized. The difference between sites of intact, rare biodiversity and low biodiversity can be as little as a single metre. Biodiversity occurs in very specific places. Even within large areas of high biodiversity, such as the Amazon, biodiversity is not equally spread, but rather topographic features, microclimates, will lead to some small areas containing niche species not found in the wider region.
- **Biodiversity is inherently geospatial; a geospatial data approach best allows the inclusion of this reality.**
- **Data** – One of the largest problems with the ‘biodiversity puzzle’ is data. We lack, globally and even regionally, both direct measures on species and ecosystem function – in-situ data, vital for establishing baselines and trend measures – and indirect proxy data which could be potentially used to support insights. Universally within this space, data cadence is a repeating issue, where often it difficult to gain access to updates at high frequency (i.e. monthly or better).

Consequently, lacking robust timely direct data, remote sensing data, primarily from satellites, has become an increasingly vital data source. Independent, robust, quantifiable, consistent and available at increasingly highly temporal and spatial resolution, it is a key resource in providing ex-situ insight at a global scale, week on week. It can also be interlinked with ecology / conservation in-situ data, which is increasingly geolocated.

A geospatial approach readily allows the ingestion of this rich, growing and improving data source, while still allowing triangulation with other datasets.

- **Scale** – The financial sector is interested in operations which span every corner of the globe. Any data solution must therefore also have global reach. Geospatial data is already generated at the global scale, allowing comparability between variables.
- **Climate Change** – Although not directly tackled in this document, climate variables are heavily interlinked with nature-related impact and vice versa; hence, understanding that connection will be increasingly important. Since much of the world of climate change data is geospatially defined, a geospatial approach can align to climate data.
- **High Cadence** – Impacts to biodiversity can occur and dissipate at a high frequency (e.g. a marine oil spill from a pipeline). Consequently, to capture such impacts before they disappear, high-frequency data is required. Earth Observation products already provide very high cadence data – daily imagery of the globe; a geospatial approach is well positioned to ingest and benefit from this data.
- **Independence** – Geospatial insight is normally entirely independent of the company itself, offering a potentially useful unbiased data source. In contrast, within self-reported ESG data (e.g. annual reports), there is an incentive to minimize reporting.
- **Critically, a geospatial approach can be data and model agnostic.** This is vital: as data changes and improves, data and models will need to be updated. In addition, this approach facilitates interoperability with third-party models to run generic or niche assessments on specific types of commercial operations within specific ecosystems.



DISADVANTAGES OF A GEOSPATIAL APPROACH

As is well documented, there are significant challenges to providing nature-relevant data insights at global scale, and geospatial solutions are no exception. While it is expected that many of these issues will be resolved as the field develops, there are significant obstacles that currently limit the extent, scale and accuracy of geospatial methods.

- **Asset Data** – There is a deficiency of asset data, either openly or commercially available, required for enabling a geospatial approach (See Page 44). The asset data which is available tends to be due to a historic commercial need. Currently only a select few sectors (e.g. power, mining, oil and gas, shipping) have robust global asset datasets. The majority of sectors (e.g. agriculture, real estate, etc.) lack globally aggregated datasets.
- **Supply Chain Data** – Almost no supply chain data is disclosed; while there has been sustained effort from commercial business intelligence providers, developing products such as FACTSET, there is still a lack of detailed, dynamic insight into 95%+ of companies' supply chains to source. Without supply chain data, the geospatial approach (and other data approaches) lacks the means to capture high tier industries' nature-related impact.
- **Observation Data** – While there is a huge volume of observational data available, there is a lack of relevancy, temporal and spatial resolution, and consistency with these datasets.⁹² On top of this, there is confusion surrounding which observational datasets, and derived metrics, to apply for defining biodiversity and ecosystem impact. However, as the commercial SRS space begins in earnest to provide data solutions for geospatial ESG application, we can expect this to change rapidly.
- **Standards** – With the field only just emerging, there are essentially no standards for data infrastructure, asset datasets, supply chain data, data security, interoperability, ownership, observational datasets, geospatial ESG methodologies, etc. However, standards do already exist across similar use cases, and as the field develops, standards can potentially be rapidly developed.
- **Business Model** – The data ecosystem of geospatial ESG is far more diverse than traditional 'ESG' business intelligence – it requires SRS, Cloud Compute, Business Intelligence asset and supply data, NGO and IGO biodiversity and ecosystem data, etc., requiring multiple open and commercial actors to collaborate and forge partnerships to generate novel data products, with an as-yet-unproven business model. A direct barrier to entry is this multi-stakeholder complexity in a space that traditionally has been controllable by a single entity. Consequently, Business Intelligence and ESG data providers may be reluctant to invest in the space due to the complexity and uncertainty around collaboration between multiple stakeholders (See Page 92).

PART 4

EXPLORING A SYSTEMATIC APPROACH TO GEOSPATIAL INSIGHT

KEY POINTS

- To provide comparable insight, geospatial ESG requires a widely agreed high-level framework, and clarity on approaches. In this section we explore various core concepts for discussion.
- Here we propose to divide insight into assets into four distinct categories – the 'IBLG': values Internal (I) to the property, Bordering (B) the property (less than 1km), in the surrounding Landscape (L) (1–1,000km), and wider Global (G) values ($\geq 1,000$ km).
- Factually stating the results within different areas relative to the asset avoids issues around causation, reducing technical complications – and potential legal ramifications – in trying to prove or assign impact to specific actors.
- We suggest that 'biodiversity' and 'ecosystem' baselines must be included, as otherwise impact/s prior to 1980, the beginnings of the SRS record, are likely to be excluded.
- Observational datasets and derived metrics could be framed in a diverse range of ways; here we suggest defining the 'environmental assets', 'direct' impacts and 'indirect' impacts within the IBLG areas.
- Significantly more complex models and insights can be developed, but for now, we attempt to select the simplest methods, to outline the vision and highlight the potential of the emerging field.
- Supply chain results can be aggregated within the IBLG approach, to provide aggregated scores for every supplier and asset within the supply chain. Existing geospatial datasets defining the location of transportation infrastructure (e.g. roads, railways) can be used to develop a standard score of the 'ecosystem and biodiversity' cost for any given route – enabling the estimation of 'transport biodiversity costs' for the shortest routes.
- The concepts outlined can be united into a single datasheet, to define results for any given asset (or aggregation).

EXPLORING A SYSTEMATIC APPROACH TO GEOSPATIAL INSIGHT

As we develop solutions to aid understanding of ecosystem and biodiversity impact, there is a temptation – as it is such a complex topic – to build ever more elaborate frameworks, models and solutions to address that complexity.

We argue the opposite. First, we should ensure we have the basics achieved – in this case, the ability to detect and assign the most serious ecosystem and biodiversity impacts at an asset level. After this, we can unravel more niche impacts and topics. However, it is important that any solutions developed are not created to the later exclusion or restriction of the integration and development of other areas, such as dependencies, opportunities and neighbouring topics (e.g. social issues, climate change) or the addition of more granular data.

This means we need a framework to work within which allows us to tackle issues around ecosystem and biodiversity impact but still enable expansion. As with the periodic table, we first should define the simpler elements, hydrogen, and helium, but ensure that the framework has the flexibility to tackle the more complex questions around impact on biodiversity and reliance on ecosystem services.

To move the geospatial ESG ecosystem and biodiversity insight forward, we raise some concepts for discussion, specifically:

- The spatial division of impact/s
 - a. Internal
 - b. Bordering
 - c. Landscape
 - d. Global
- Division of observational data
 - a. Baselines
 - b. Environmental context
 - c. Direct impacts
 - d. Indirect impacts
- Supply chain and transportation (infrastructure) impacts
- Uniting components

The concepts outlined here are to be viewed as draft concepts to encourage debate and catalyse efforts; each component will need careful consultation, peer review, standards, benchmarking, etc. to test its validity.

SPATIAL DIVISION OF INSIGHTS

To simplify the complexity in assigning ecosystem and biodiversity impact to assets, it is useful to consider using fixed (or relative ratio) area values to capture and categorize impacts. Here we propose the following area definitions (Figure 22).

- i) **Internal (I)** – values reported within the property boundary of the asset.
- ii) **Bordering (B)** – values reported in the immediate area bordering the property (\leq km)
- iii) **Landscape (L)** – values reported within wider landscape/s (1–1,000km)
- iv) **Global (G)** – values for a given metric with impact beyond \geq 1000km (e.g. GHG emissions).

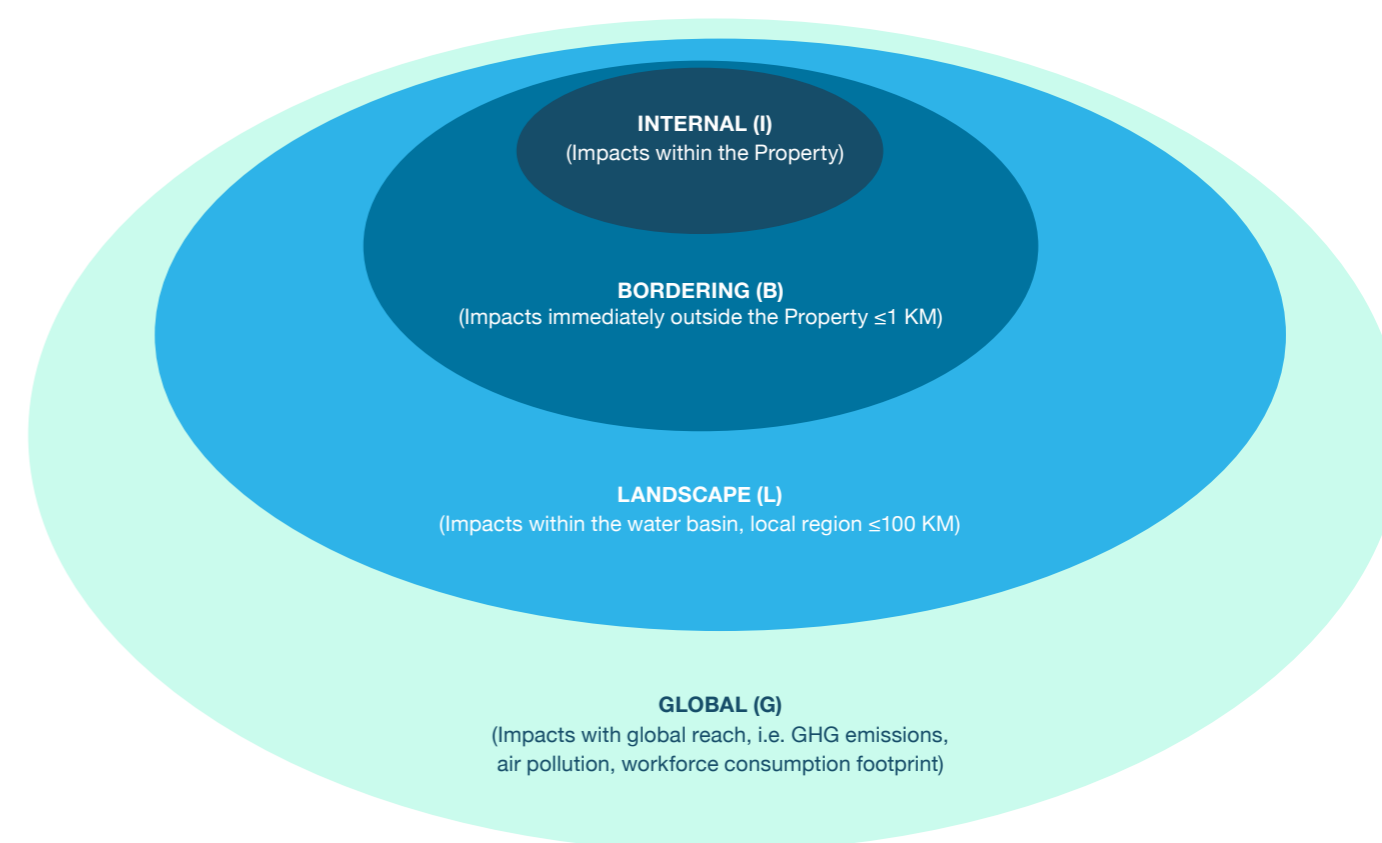


Figure 22 – Illustration outlining the proposed area divisions for terrestrial commercial assets – values within the property, bordering the property (less than 1km), regional values in the surrounding landscape (1 –1,000km) – and wider global values (\geq 1,000km).

The division of impact into consistent areas is, from a technical perspective, simple and comes with several significant advantages. First, it helps resolve issues around causation. Rather than attempt to prove the causation of an asset's impact, we can reduce the complexity of the challenge by just factually stating what has occurred within different area boundaries relative to the asset. This resolves how to assign issues of unclear origin – for example, deforestation can occur alongside the border of a palm oil plantation; this cannot be assigned to the asset itself as it is outside the property, but it can be captured as a 'border' impact. By using the same consistent approach for all terrestrial assets globally, no specific holder or asset class is biased.

Second, it allows the consistent development and application of landscape insights, vital for dealing with issues around cumulative impact and the shifting magnitude of localized impact (See Page 86). Impacts within a fixed area designation (e.g. a specific water basin) can be captured to provide dynamic, consistent and comparable insight into the asset's wider landscape condition, which can then be used to adjust IB impact weightings (See Page 88). Third, by dividing out 'global' impacts, those which are which effectively ubiquitous in Earth systems (e.g. GHG emissions), it provides a direct means for users to easily consider the difference between an asset's, or companies 'localized' impacts, within the context of 'global' impacts (e.g. habitat loss vs. GHG emissions).

In the next section, we'll briefly run through each of these (IBLG) area designations, exploring a few examples.

INTERNAL (I) INSIGHT

Any values as reported within the property boundary of the asset itself.

In many cases, (I) results will report relatively static values. This is because most assets – fields, factories, real estate – tend to clear all habitat occupying the near full (95%+) extent of the property boundaries. This is because land is expensive, and we tend to optimize the use of land, particularly in urban areas, where the vast majority of asset numbers are located.

If we consider different asset types, we can conceptualize the types of data reported (Figure 23).

All assets, take up a spatial area; hence, the historic ‘ecosystem or biodiversity baselines’ (e.g. AD 1500, 1990, 2000, 2010, etc.) or regional uniqueness can be measured to provide a baseline. From there, any post-1980 observational datasets (e.g. land cover, ground carbon, water coverage, etc) can be measured for the sites – capturing and defining over time any direct impacts (habitat clearance / restoration) over the last 10–30 years⁹³ within these property boundaries.

After considering direct impact, it is possible to consider indirect impact, via actual or modelled observational data insight. This is where biome and sector specific metrics are useful. For example, we could look to measure the infra-red heat profile of the shopping centre to estimate its likely power consumption or the extent of carbon loss from deforestation.

In many cases, indirect impacts may not have an ex-situ data solution, where it is simply not possible to measure some variables (e.g. heavy metal soil pollution). This is a reality of any ex-situ data solution, where some measures can only be achieved with in-situ, ground data. To aid filling these shortfalls, it may be useful to use Landscape (L) insight to provide some level of insight (See Page 88) and/or to fill those gaps through data triangulation (See Page 55).

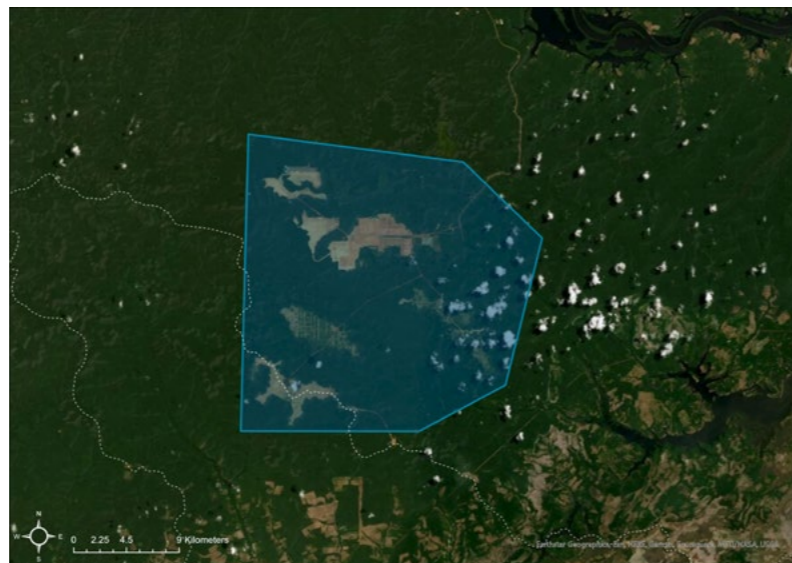


Figure 23 – Satellite images illustrating three different types of asset classes, top), shopping centre, Cairns, Australia; middle), field, Madhya Pradesh, India; both showing their true property boundaries (orange); bottom) bauxite mine, Pará, Brazil with estimated boundaries (blue).

BORDERING (B) INSIGHT

Any values reported in the immediate area bordering the property ($\leq 1\text{km}$).

If we consider the three examples in Figure 24, we can see that by applying a buffer of 1km to an asset, we can use the observational data captured to provide the immediate context to the asset.

The immediate area around any given asset provides insight into its potential for wider direct or indirect impacts; if no existing habitat is surrounding the asset, its likelihood for expansion and localized indirect impact is, generically speaking, diminished. If, however, as in the case of the mine, it is surrounded by pristine habitat, it’s potential increases. It is possible to define what is within this bordering area and any changes to it, via observational datasets, such as land cover, biomes, ecosystem, species data, etc., to provide insight into the past and current context of the asset.

One consideration to note: when applying ‘buffers’ for (B) insights, it may be useful to use a more sophisticated approach to determine the extent of the buffer, based on the asset’s size or sectorial risk profile, as it might be illogical to apply a 1km buffer to those assets with a smaller footprint (e.g. 10 m²). To keep the concept simple for now, we suggest a standard 1km buffer – but it is likely this can be improved.

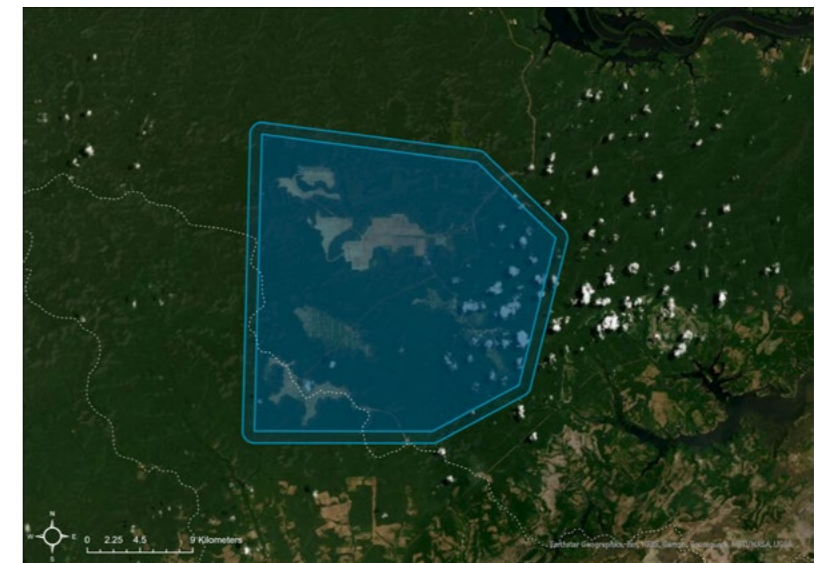


Figure 24 – Satellite images illustrating three different types of asset classes: top) shopping centre, Cairns, Australia, middle) field, Madhya Pradesh, India, with their true property boundaries and 1km buffer (orange); bottom) bauxite mine, Pará, Brazil with estimated boundaries and 1km buffer (blue).

LANDSCAPE (L) INSIGHT

Any values reported within wider area designation/s (1 –1,000km).

Understanding what impacts have occurred within an asset's property (I), and just outside (B) is, of course, important. However, this understanding also needs to be put into context of the wider landscape (See Page 86). If, for example, an asset is operating in a landscape with stable forest cover, its IB impacts are likely to remain constant. If, however, forest cover is being lost dramatically in the wider region, then the importance of any remaining forest increases, as do the significance and magnitude of any ongoing or novel localized (IB) impacts on the remaining forest.

Here we propose the use of water basins and sub-basins⁹⁴ as naturally occurring nested non-subjective divisions of the landscape (Figure 25), as water basins, controlling the flow of water, naturally often aggregate impacts within them, and biodiversity and ecosystems tend to loosely align.



Figure 25 – Global map showing the HydroBASINS division of the world into water basins and nested sub-basins (Level 6).

To develop landscape insight, it is simply a case of assigning each asset to the 'landscape/s' it is located within⁹⁵; in this case we propose sub-basins (Level 6). 'Landscape values' for those areas can be generated using observational data and trends detected (e.g. ongoing year on year habitat loss). This provides insight into both cumulative impacts and the relative magnitude of impacts within a given landscape, allowing the adjustment of the impact weightings and aiding in the capture of the magnitude of localized impacts within the context of wider scale trends (See Page 86).

Figure 26 – Simple illustration of the area within the water basins (Level 6) of three different types of asset classes, top) a shopping centre; middle) agricultural field with their true property boundaries and 1km buffer (orange), and bottom) a bauxite mine with estimated boundaries (blue).



GLOBAL (G) INSIGHT

Values for a given metric with non-localized impact beyond 1,000km (e.g. GHG emissions).

In some cases, impacts do not remain bound to a specific area but dissipate into the Earth's systems, for example, air pollutants and emissions, such as NOx or GHGs, that disperse into the atmosphere. Such impacts are effectively 'global' in range – where GHGs emissions are driving global issues such as climate change and ocean acidification.

These metrics are assigned to (G) and allow users to consider, and make their own determination as to the significance of, the more localized impacts against global impact/s. Some assets and companies are likely to have low localized impacts but high global impact (e.g. aviation), and vice versa.

DIVISION OF OBSERVATIONAL DATA / METRICS

To simplify the complexity in understanding what environmental assets, the landscape condition, and what direct and indirect impacts are associated within the IBLG areas for a given asset, its useful to consider fixed thematic divisions. Here we consider the following:

- **Baselines** – The historic 'biodiversity' or 'ecosystem' values.
- **Environmental Context** – The extent of defined environmental assets present.
- **Direct Impacts** – Any natural or human direct impacts.
- **Indirect Impacts** – Any natural or human indirect impacts.
- **Additional Variables**
 - **Reflections On Supply Chain and Transportation (Infrastructure) Impacts**
 - **Supply Chains**

This provides context of any asset, allowing the aggregation of data points, which can be **quantified** into comparable formats (See Page 82).

BASELINES

If we accept that a data- and model-agnostic approach is vital – needed as different actors will inevitably wish to use different asset, supply chain and observational datasets, or change and upgrade these, and apply differing models for tailored social, climate, biodiversity and ecosystem insight – we will need a framework which allows flexibility in the data and models applied, but still has uniting standards that ensure approaches are interoperable and comparable. As a central component of this, we propose the need for consistent 'baselines'⁹⁶ to compare current ecosystem and biodiversity values against.

ESTABLISHING GLOBAL BASELINES

If we do not apply a baseline, a global layer which tells us the original ecosystem and biodiversity site value, what we're effectively doing is focusing on any impacts after the 1980s. This is when the satellite imagery record began, and in most cases, due to data quality, we'd be only assigning destructive impact post 1990, if not 2000, when many key geospatial observational data products started in earnest.

So, which is the right year?

If we set a date, perhaps one which works for the data available, we're effectively determining that any identifiable impacts, such as major habitat loss, before that date are non-assignable. This creates a range of problems. First, it is aggressively unjust – it suggests that those nations (often the developed nations) which had already destroyed many of their environmental assets prior to the 1980s are free to use their cleared lands as they wish for economic advantage, whereas those who had not (often developing nations) will have any future impact assigned to their 'environmental performance'.

Second, failure to capture historic impact will create biases in assessment of those sectors, companies and supply chains which are within areas cleared prior to a feasible date of measurement. As we move towards estimating the ecosystem and biodiversity impact of companies, supply chains, soft commodities, etc., against each other (peer-to-peer comparison), factoring this original cost will be essential. Finally, from a planetary management perspective, the Earth's systems do not make any such temporal distinction – any ecosystem loss or degradation counts within the local, regional and global system.

The central issue with establishing baselines is that species distributions and ecosystem extent have been changing both naturally and by humanity's influence for thousands of years.⁹⁷ For example. England's anthropogenically-driven forest loss is now thought to have emerged, significantly, over a thousand years ago.⁹⁸ As a result, we lack granular global data for how biodiversity was previously arranged. One solution to this is to step away from current land cover and species range approaches for defining current biodiversity and ecoregion extent, and instead focus on quantitative variables that predict biodiversity (See Page 70). Although not conceptually critical, we suggest a theoretical historic baseline of 1500AD, as this is the baseline used for assessing species extinctions within the IUCN Red List.

Within this document we propose a possible approach to this not as the solution, or as a novel development, but to encourage debate and others to rapidly develop 'Global Baselines' for geospatial ESG application. The reason is twofold: first, the development of robust baselines will take significant collaboration and wide agreement, and will require scientific peer review. Second, since the geospatial approach is data-agnostic, we can and should encourage multiple baselines. From a data perspective, the only requirement is that each has an identifiable name, and that is included in end results (e.g. 'baseline V2 applied'). Baselines can be updated, and users will be able to select the baseline they consider the most robust for their needs.

Inevitably, over time, a small number of baselines will emerge as the most authoritative, and it's likely they will have a high degree of consistency between them.

CONSIDERATIONS FOR BASELINES

Here we outline one potential way forward to developing a global baseline, to catalyse debate. For geospatial ESG applications, ideally, we need a high-resolution global layer (10m). To develop such a product, it is first useful to consider the patterns that govern the global distribution of biodiversity.

GLOBAL BIODIVERSITY DISTRIBUTION

For over 200 years, ecologists and biogeographers have struggled with the question, What determines the global distribution of biodiversity?⁹⁹

Entire fields of research, thousands of papers, have been dedicated to understanding the spatial distribution of biodiversity, often as measured by numbers of species in an area (species richness). While the field is complex and no consensus has yet been reached, it is enough here to point out the general and well-documented patterns, the known relationships between biodiversity and physical variables (Figure 27). It is important to note that we are not interested in *why* these patterns exist, as much of the research is focused on, but the value in using these known patterns to predict global patterns of 'pre-human impact' biodiversity.

Very simplistically, some key factors are:

- **Area** – as area increases, biodiversity increases: the larger the area (land or sea), the greater the opportunities to support species richness and speciation.
- **Latitude** – the increase in species diversity from the poles to the equator has long been well documented, referred to as the latitudinal diversity gradient (LDG).¹⁰⁰ Hillebrand's 2004 meta-study of 600 studies¹⁰¹ showed that species richness increases towards the equator but that the trend is stronger regionally than locally, and although the trend does not differ between northern and southern hemispheres, it is asymmetric, not quite aligning to the equator.
- **Elevation** – species diversity decreases with increase in elevation.
- **Rainfall** – as rainfall increases, biodiversity increases.

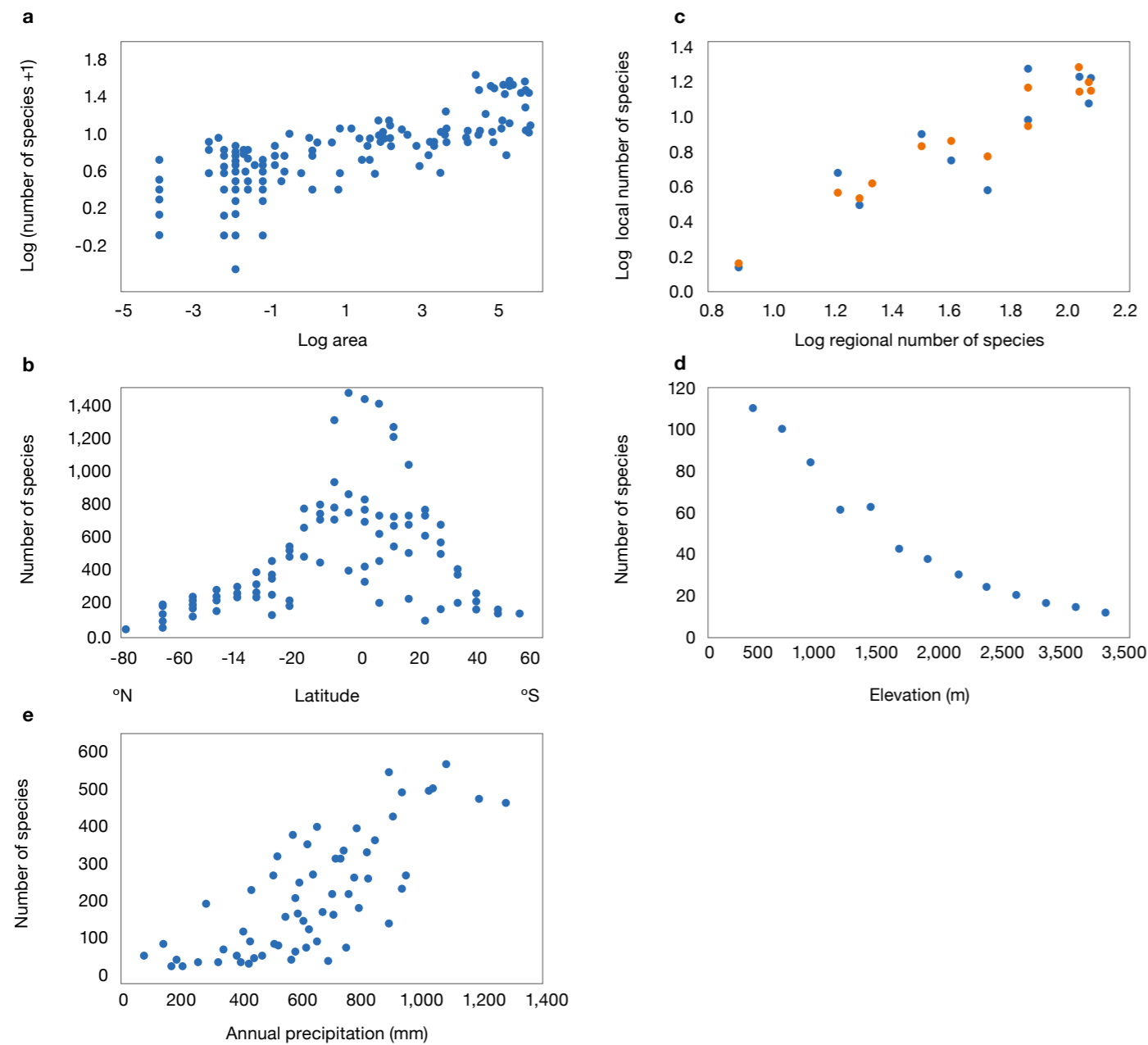


Figure 27 – From Gaston, 2000 – graphs showing spatial distribution patterns in species richness. **a.** Species–area relationship: earthworms in areas ranging from 100m² to >500,000km² across Europe¹⁰². **b.** Species–latitude relationship: birds in grid cells (~ 611,000km²) across the New World¹⁰³. **c.** Relationship between local and regional richness: lacustrine fish in North America (orange circles, large lakes; blue circles, small lakes)¹⁰⁴. **d.** Species–elevation relationship: bats in Manu National Park & Biosphere Reserve, Peru¹⁰⁵. **e.** Species–precipitation relationship: woody plants in grid cells (20,000km²) in southern Africa¹⁰⁶.

VALUE OF EXISTING PRODUCTS

There are many differing approaches, already achieved, that might be relevant to developing global baselines for geospatial ESG applications. For example, aggregated species range maps have long played a role in ecology, and today there are multiple data products, defining areas of interest such as global biodiversity richness^{107,108} (e.g. number of species per km²) or defining the original extent of ecosystem and biome ranges and conditions (Figure 28).¹⁰⁹

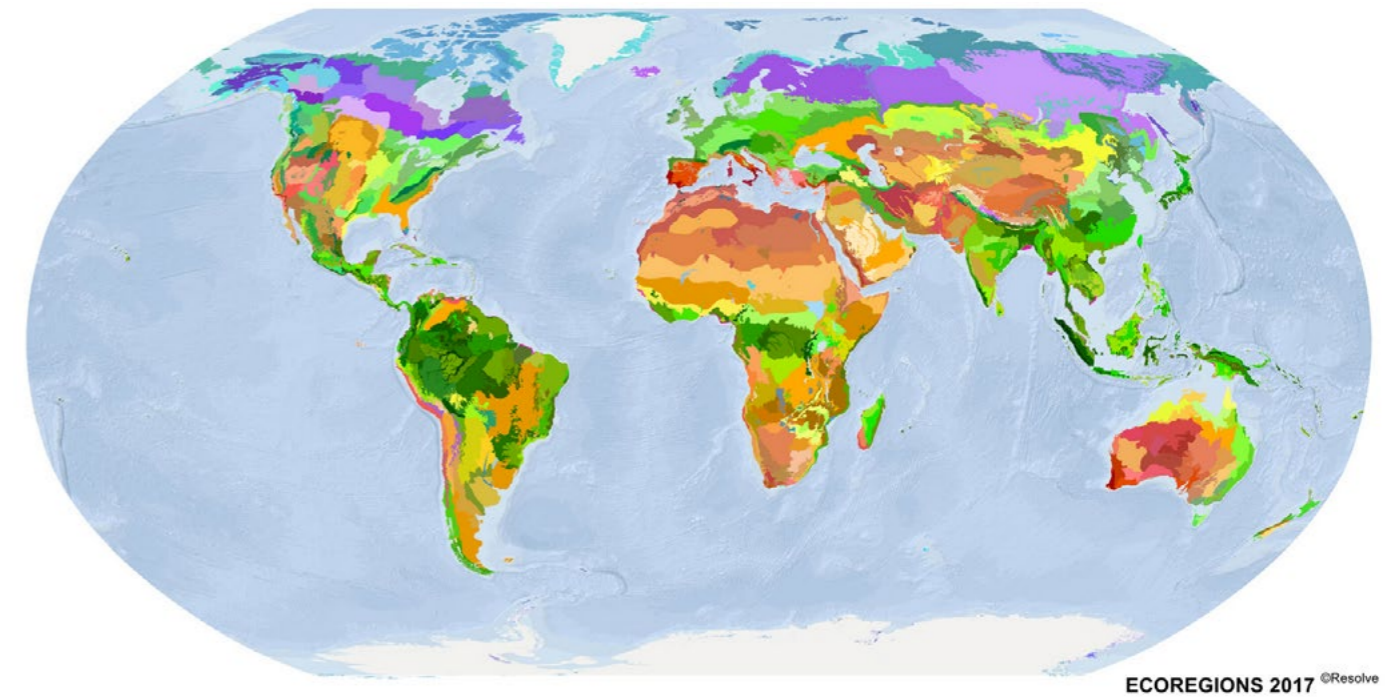


Figure 28 – From Dinerstein, et al., 2017¹¹⁰. 846 global ecoregions nested within 14 terrestrial biomes.

Such area definitions can be used to estimate the original extent of species richness or the original extent of varying types of ecosystems and their traits and, importantly for conservation purposes, used to assess the extent of remaining habitat within these regions. Any existing data product can potentially be integrated with other data, or approaches, to refine insight.

BOX 5 – DEVELOPING A BASELINE FOR BRAZIL

For geospatial ESG applications, we need create one or multiple historic points of reference, either on the original ‘biodiversity’ values for a given area (e.g. richness, abundance) and/or the original ecosystem present and its associated values (e.g. habitat type, biomass, species richness, abiotic uniqueness, etc.). These insights can be arranged at a global scale or normalized within a given area such as an ecoregion or biome – or potentially a water basin, to align to the IBLG approach.

To illustrate the concept, we estimate Brazil’s abiotic uniqueness. Here using ArcGIS Pro 3.0.2, we took a Digital Elevation Model at 250m resolution and defined the uniqueness of the physical elevation, slope and aspect within fixed range categories. We then compiled these three variables together to give us the ‘physical elevation uniqueness’ for every cell (Figure 29).

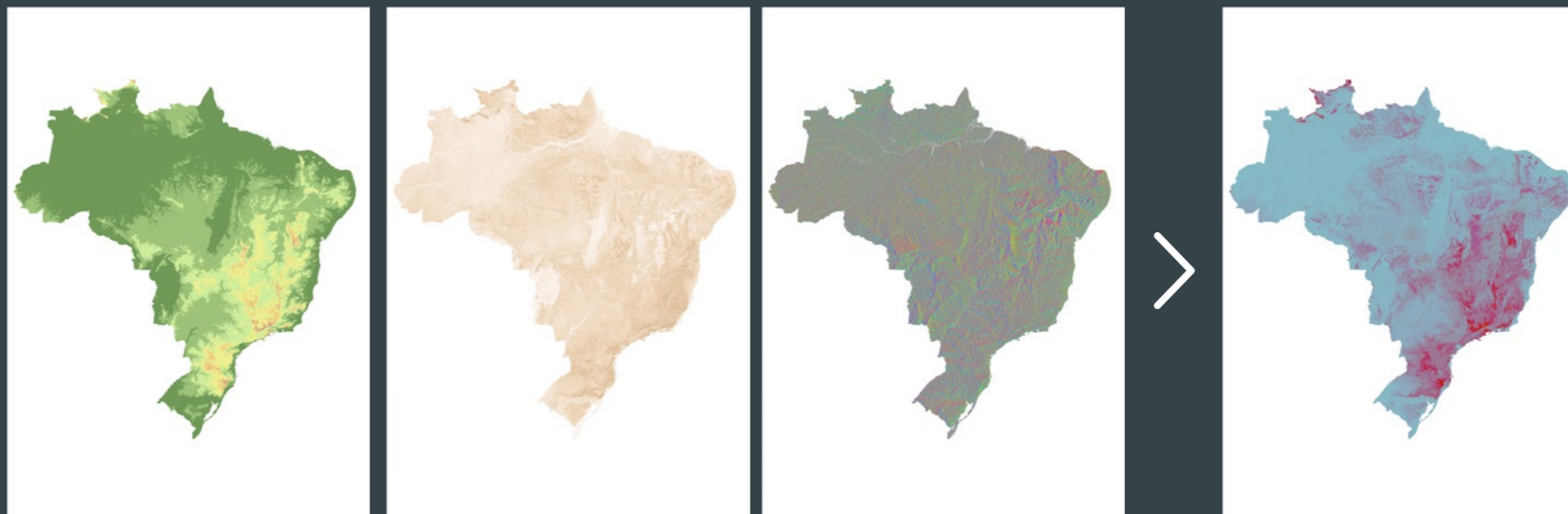


Figure 29 – The uniqueness of each cell according to elevation, slope and aspect, within Brazil.

Using the same approach we defined the ‘climatic uniqueness’ of each cell according to its rainfall and temperature for Brazil (Figure 30). Here we only consider two variables, more can and should be considered.

This provides only an outline of the concept, and many more variables (e.g. freshwater) need to be considered and applied intelligently. For now, we can integrate these simplistic measures of the ‘climatic’ and ‘physical’ uniqueness of Brazil (Figure 29 and 30) and use these values alongside biodiversity or ecosystem data, or modelled against the global biodiversity distribution patterns (See Page 70). Such an approach should almost certainly not be conducted on a national scale but at the biome, ecoregion or water basin and sub-basin levels, as from a biodiversity perspective, the uniqueness of a cell value is mostly only relevant to the surrounding ecosystem. For example, high elevation in the south of Brazil is less relevant to Amazonian biodiversity distribution – where localized unique climatic or physical characteristics are likely to offer habitat niches and contain irregular biodiversity (Figure 31).

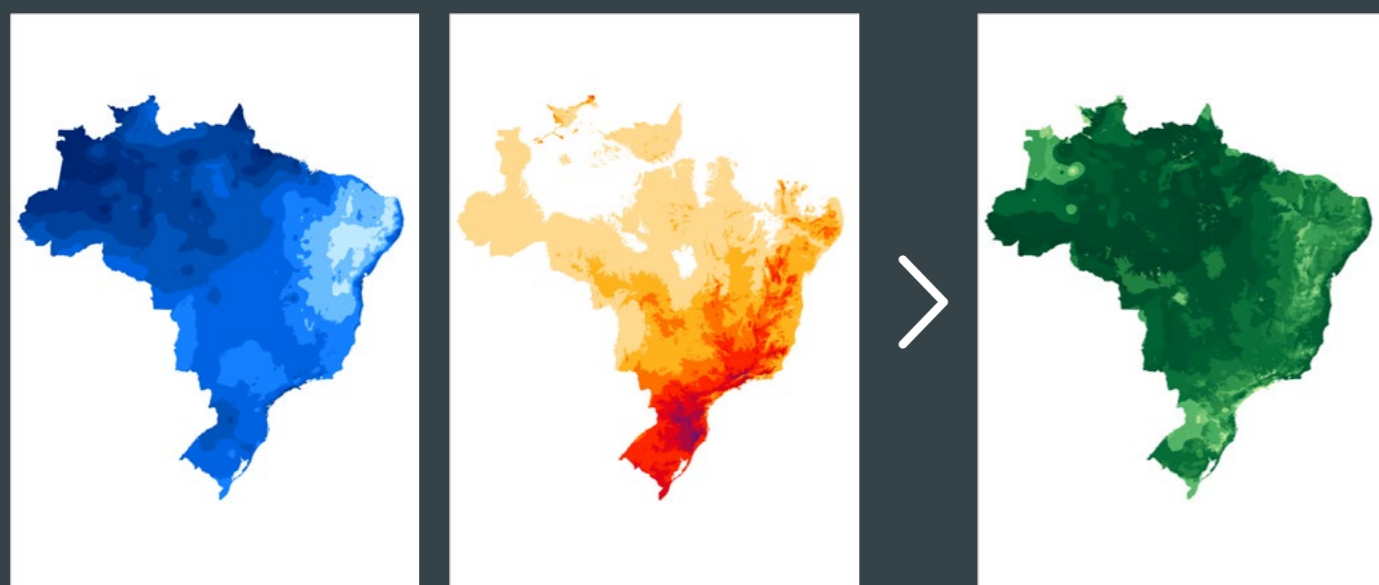
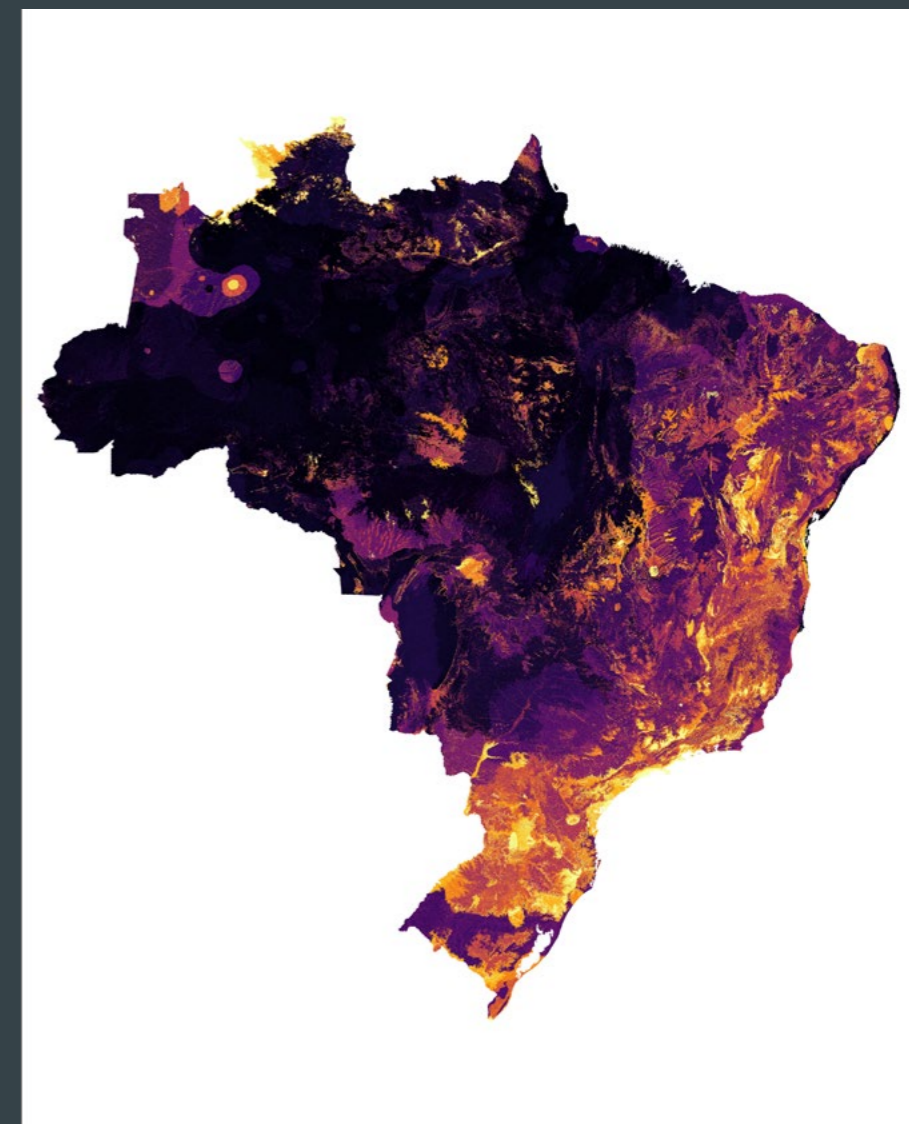


Figure 30 – Combined together, the uniqueness of each cell according to rainfall and average annual temperature, within Brazil.

The key point here is that the development of robust baselines for geospatial ESG application is possible with existing data, where high-resolution Digital Elevation Models (DEM) and data on other abiotic and biotic variables are available. Of course, results can be compared back to actual biodiversity data and iteratively developed. Indeed, there are existing and ongoing work programmes and organizations (GEO-BON¹¹¹, Half-Earth Project Maps¹¹², Nature Serve USA Map of Biodiversity Importance¹¹³) developing solutions, or alternative solutions in this space or related areas, that could potentially be utilized.

What must be stressed is that the ‘conservation community’ must collaborate and agree on what product/s should be used as global biodiversity baselines for geospatial ESG applications. Total consensus is not necessary, multiple products can be used, including site specific and regional baselines – however, we need at least one robust, widely accepted global baseline for real-world use.

Figure 31 – A rough approximation of the climatic and physical uniqueness of Brazil; an approach which could be used to infer the potential biodiversity and ecosystem uniqueness of a given cell and converted into biodiversity richness by integrating global biodiversity distribution models.



ENVIRONMENTAL CONTEXT

Within the IBLG area delineations it is important not just to define the baseline and impacts occurring within given area delineations but also the environmental variables present and any changes over time. These can be simplistic measures, such as in which biome the asset is located (e.g. Amazon Basin, Temperate Forest) or SRS insight, such as extent of forest cover or mangroves, or even more complex measures only recently possible with cutting edge SRS (e.g. structural biomass).

There are literally thousands of potential observational datasets which could be applied to provide ‘environmental context’ to a given asset. Since our approach is data- and model-agnostic, there is no definition of which should be applied or a limit on the number of datasets applied; however, it seems likely that ‘less is more’, at least initially, where it will be easier to benchmark. In many cases, an effective shortlist of the most robust, regularly updated products is emerging organically: due to data consistency, availability and accuracy, we repeatedly see the same ‘nature-related’ geospatial datasets applied within financial, ESG-related applications.

That said, as we move forward, many of these datasets would benefit from improved data cadence and resolutions to improve geospatial ESG insight (See Page 47).

DIVISION OF IMPACT

Ecosystems face a vast range of impacts.¹¹⁴ Various frameworks and impact classification schemes have emerged to provide structure and insight, many built from the IUCN Threat Classification Scheme, such as that used in ENCORE. These are of course useful; below are ENCORE impact drivers:¹¹⁵

- Disturbances – (noise, light pollution)
- Freshwater ecosystem use – (occupation, use of freshwater habitats)
- GHG emissions – (CO₂, CH₄, N₂O, SF₆, HFCs, PFCs, etc.)
- Marine ecosystem use – (occupation of marine, area of aquaculture)
- Non-GHG air pollutants – (PM_{2.5}, PM₁₀, VOCs, NO_x, SO₂, CO), etc.
- Other resource use – (mineral extraction, wild-caught fish)
- Soil pollutants – (volume of waste matter discharged and retained in soil over a given period)
- Solid waste – (waste by classification (e.g. non-hazardous, hazardous, and radioactive), by specific material constituents (e.g. lead, plastic), or by disposal method (e.g. landfill, incineration, recycling, specialist processing)
- Terrestrial ecosystem use – (occupation of terrestrial, area of agriculture by type, area of forest plantation by type, area of open cast mine by type, etc.)
- Water pollutants – (nitrates, phosphates, heavy metals, chemicals, etc.)
- Water use – (volume of groundwater consumed, volume of surface water consumed, etc.).

It is important to note a distinction here: natural events (e.g. earthquake, volcanic eruption) can also cause significant ecosystem and biodiversity impacts. As we look to assign impact to specific assets, it may in certain cases become important to differentiate these: a farmer may not be responsible, nor the decision maker, on whether a large area of woodland is lost within their property to a landslide, natural wildfire, storm damage, etc.¹¹⁶ Determining responsibility as to whether such natural activities are ‘an act of god’ or the results of human activity or mismanagement is a challenge.

As a starting point to simply the impact equation, we suggest the concept of dividing all ecosystem impacts (natural or human-driven) into two types, ‘direct’ and ‘indirect’.

DIRECT IMPACTS¹¹⁷

Direct impacts are the permanent (5+ years) loss of habitat, such as felling a forest, slash and burn agriculture, deliberately burning down shrubland, bulldozing for construction, mining – anything which for the immediate future removes the prior existing habitat. It could be a small area of the ecosystem (1ha out of 10000ha), or it could be large area. Such impacts are often easily detectable by SRS and so are often easier to detect, scale and assign within the IBL, (i.e. the mine cleared this much habitat for the mine, and this area of habitat for its access road).

Direct impacts, while varied in scale and consequence, are arguably from a technical data perspective the simplest part of the ‘biodiversity’ data challenge to get right, being some of the most easily measured from ex-situ data. However, these impacts tend to occur at the very end of supply chains, often in assets held by non-listed actors, in the primary industries. Consequently, inclusion of supply chains assets, is challenging but vital to ensure a more accurate estimation of high tier sectors impact (See Page 38).

INDIRECT IMPACTS

Indirect impacts are far less straightforward but vital in understanding the holistic nature-related impact of an asset. **An indirect impact is any impact that, without significant habitat destruction, limits or lowers ecosystem condition.** They are many different types, and they can cascade silently through an otherwise healthy-looking ecosystem. For example, heavy metal pollution seeping into waterways causing reduction in river dolphins’ breeding success. Examples of potentially reductive impacts include over-extraction of freshwater, noise pollution, introduction of invasive species, poaching, bush meat hunting, tourism, fragmentation, disease, pesticides, oil spills, shipping traffic or globally overarching impacts such as air pollution, climate change and ocean acidification.

Indirect impacts are incredibly complex, as outlined in Part One of this paper, varying in realised impact according to the specific impact event and specific ecosystem in question. Many of them cannot be detected via ex-situ data solutions, requiring detailed in-situ ground, soil, water, air and species sampling and long-term research.

For example, illegal gold mining in the Amazon, which uses mercury in the gold purification process, creates mercury pollution which accumulates in the landscape and food webs.¹¹⁸ It’s thought that 15% of the region’s gold comes from illegal mines, and the volumes of pollution this generates are not trivial. Mercury, highly toxic, contaminates plants and animals¹¹⁹, known to lead to reduced reproductive success and increased mortality.¹²⁰ In a study of catfish, 97% were found with ‘high’ levels of mercury – on average, five times higher than recommended levels for human consumption.¹²¹ Annually across the region, it is estimated that 130,000–220,000 healthy human lives are lost due to disability induced by moderate or chronic metallic mercury intoxication.¹²² The nightmare that is mercury pollution cannot be overstated: it is a volatile chemical that does not disintegrate over time – often pollution is irreversible and difficult to contain.¹²³ Halfway around the world, in the backcountry of New Zealand, a micro-scale pollution issue is causing trouble for one species. Lead pollution is a threat to the Kea, an endangered parrot. Thought to be attracted to the metal’s sweet taste, the birds find, and chew lead fixtures introduced into their habitat, on mountain huts, mines, etc., It has become present in their blood, causing a range of health issues and mortality,¹²⁴ in part – amongst other threats, such as invasive species – limiting their survivability.

These are two examples of indirect (reductive) impacts of different magnitudes – silent impacts that can go unseen within an otherwise ‘healthy-looking’ ecosystem. While it might be possible to create proxy metrics for mercury pollution (e.g. extent of illegal mining sites), understanding the indirect, reductive impacts of mercury pollution on biodiversity and ecosystem condition, and how it exacerbates other issues, will require long-term and detailed in-situ field study. While in the case of the Kea, no ex-situ, SRS-driven solution can capture and report such a hyper-specific indirect impact, nor may various such hyper-niche topics be justifiable for inclusion. As we’ll outline on Page 94, to begin to surmount such specificity issues, we envision an ‘app store model’, where users, or machine rationalisation, will be able to select from thousands of third-party-developed datasets and models to draw, generate or create specific estimates of direct and indirect impacts from specific asset types operating within very specific ecosystems.



Gold mining barge in the Tapajós River, Juruena National Park - Maués, Brazil
© Andre Dib / WWF-Brazil

Above - Maxar WorldView-2 satellite image showing mining barges on Pure River, Colombia, on June 2, 2021. Satellite image © 2022 Maxar Technologies.

(See: Hettler, B. (2022))

ADDITIONAL VARIABLES

REFLECTIONS ON SUPPLY CHAIN AND TRANSPORTATION (INFRASTRUCTURE) IMPACTS

Infrastructure assets (e.g. railways, powerlines, undersea cables, roads, etc.) can be assessed as standard within the geospatial ESG approach. However, transportation infrastructure has an additional application within geospatial ESG – providing insight into the biodiversity and ecosystem implications of the movement of goods between assets for supply chain assessments.

As we connect supply chains together, it becomes important to factor in the ecosystem and biodiversity implications of the infrastructure (e.g. roads, rail, ports, airports) used to transport goods, in terms of shortest route distance.¹²⁵ Rather than running an assessment for each unique supply chain, it seems logical to simply define the biodiversity and ecosystem metrics (e.g. habitat loss per km, fragmentation, wilderness exposure, etc.) for every road, railway, and transportation hub globally. These metrics can then be immediately aggregated for any given route, to provide insight into the overall ‘biodiversity impact’. Key variables, such as if the first connecting node is unique (e.g. a road built solely for one asset, e.g. a mine access road) can be highlighted; these are important – often cutting through previously untouched areas. This approach could follow the IBLG methods, focusing on the internal and bordering impacts of a linear infrastructure (See Page 62). However, it seems probable specific metrics and methods will need to be developed for defining the biodiversity and ecosystem ‘costs’ associated with different types of linear infrastructure.

Interestingly this process has a parallel where insurers have defined extreme weather vulnerability (based on historic wind, rainfall, etc., natural hazard data, and climate change data) of linear infrastructure, to define specific assets’ vulnerability.

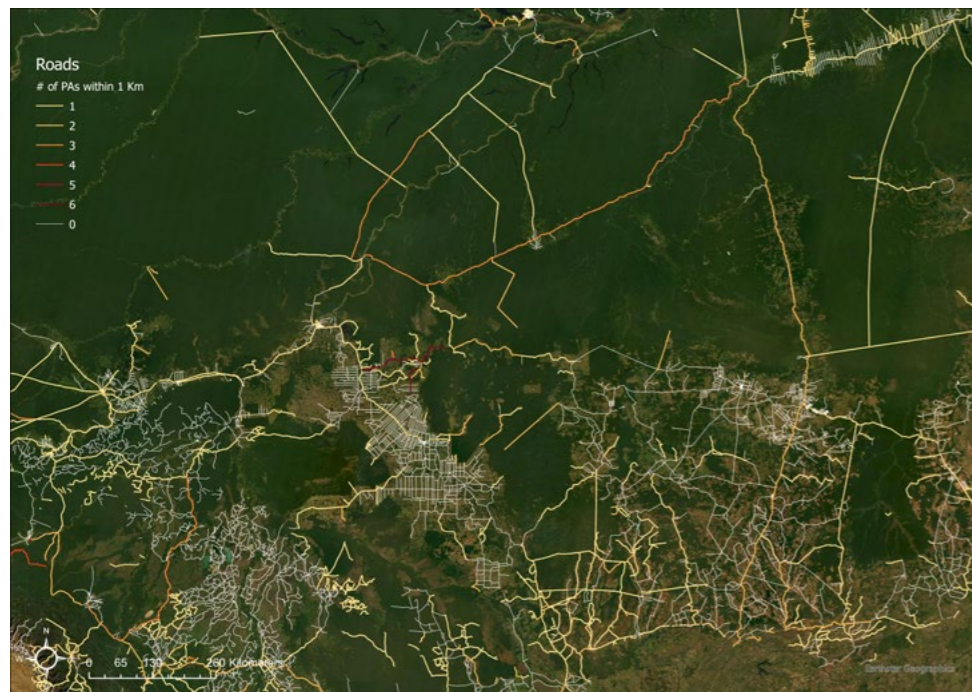


Figure 32 – Illustration of the concept of developing global scoring for transportation routes, in this case roads, allowing easy aggregation for any given supply chain transportation route. Here we look at the combined IB impacts of ‘protected area exposure’ of roads in South America. Of course, more complex, insightful approaches should be developed.

Since there are robust, open datasets on linear infrastructure, an opportunity is present for the community to collaborate to agree on and create open global datasets on linear infrastructure’s ‘biodiversity and ecosystem impacts’ for geospatial ESG applications. Again, consensus is not required; multiple products can be used – however, a widely accepted global standard dataset would most likely support adoption.

SUPPLY CHAINS

Although not explored in detail in this paper, we should note that a geospatial ESG approach theoretically has no issue with the integration of geospatially derived supply chain insights, where each supplier’s asset/s can be assessed following the same method as for an owned asset. Essentially the hundreds, or maybe tens of thousands, of suppliers are assessed, and their values aggregated (Figure 33). The distance between suppliers, and the transportation metrics can potentially also be included (See Page 78).

The major challenge with supply chains is access to data, where even commercial providers have struggled to make headway within this space. Until detailed and accurate data can more readily be accessed, supply chains will remain problematic to factor into any ESG solution. **Within this document, we make the case that secure one-to-one data sharing offers the highest potential for FIs to gain access to supply chain data within the emerging geospatial ESG data ecosystem (See Page 102).**

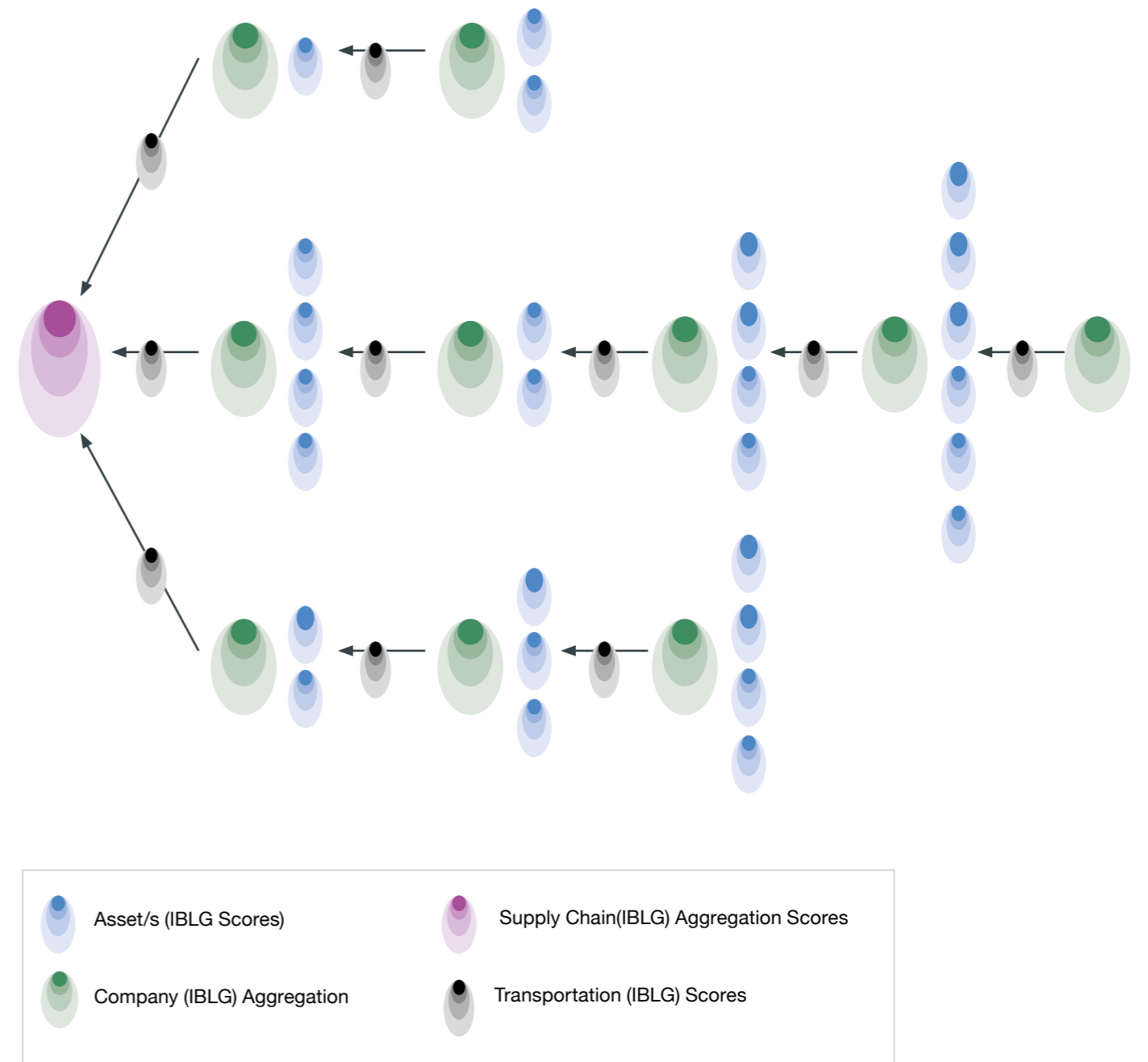


Figure 33 – Simple diagram outlining how supply chains can be assessed within the IBLG geospatial ESG approach, potentially including transportation insight.

UNITING COMPONENTS

If we take an asset, the IBLG area divisions, baselines, environmental context, and observational data landscape condition insights, the direct and indirect impact divisions and a temporal component, we emerge with something like the following:

Biodiversity Impact Insight	Baseline Measures																Environmental Context								Ecosystem Condition (Triangulation)												Direct Impacts												Indirect Impacts																																							
	Asset Area Values (Sq Km)				Baseline Historic (CECAS V.3.2)				Baseline 2000				Baseline 2020				Biome		Ecoregion		Land Cover		Extent of Intact Forest Landscapes		Metric 1 - Leaf Stress Index		Metric 2 - Net Primary Productivity Consistency		Metric 3 - Above-ground Biomass Consistency		Metric 4 - Vegetation Height Consistency		Metric 5 - Transpiration Consistency		Metric 6 - Ecosystem Structural Variance		...		Metric 1 - Habitat Loss		Metric 2 - Forest Loss / Gain		Metric 2a - Forest Loss (Primary Forest)		Metric 3 - Fragmentation		...		Metric 1 - Disturbance - Light Pollution / Night lights		Metric 2 - GHG / Air Pollution (CO2, CH4, N2O, SF6, HFCs, PFCs, etc.) (PM2.5, PM10, VOCs, NOx, SO2, CO)		Metric 3 - Water Extraction		...																																	
	I	B	L	G	I	B	L	G	I	B	L	G	I	B	L	G	I	B	L	G	I	B	L	G	I	B	L	G	I	B	L	G	I	B	L	G	I	B	L	G	I	B	L	G	I	B	L	G	I	B	L	G	I	B	L	G	I	B	L	G	I	B	L	G	I	B	L	G	I	B	L	G	I	B	L	G	I	B	L	G	I	B	L	G	I	B	L	G
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A few points are useful to consider:

- Temporal Component** – Any approach used must be able to consider impact over time. Here we loosely suggest from 1985 onwards, aggregating results to quarters. Inevitably different metrics will have differing frequencies (some daily, others annually) driven by the technology, data product and the impact being assessed.
 - Understanding when an impact occurred is important; first it gives the ability to track how specific impacts evolved, providing an understanding of frequency of the impact/s. Second, it allows the correlation to temporal values, such as changing vulnerabilities (e.g. breeding season) and ownership. Where ownership of assets changes over time, a current owner may not be responsible for past impacts.
- Fixed Area Definitions** – We suggest the IBLG approach, but of course, any area division can be applied – including biome, regional and or sector specific delineations. Ideally, we would see wide use of the same area standards across the financial sector, to enable interoperability and comparison.
- Baselines** – Both historic (See Page 68) and actual baselines can be applied; here we show three in use, historic (1500AD), 2000 and 2020. If assets were developed or altered post-2000 or 2020, these baselines give the advantage of more accurate comparison insight. Site specific or regional baselines could also be applied.
- Environmental Context** – The use of internal (I) bordering (B) and landscape (L) area delineations offers insight into the context (and changing context over time), of the immediate and wider position of an asset and the shifting magnitude of its impact. This data arrangement has the benefit of linking closely to other topics, such as dependency.
- Landscape Condition** – While we make no statement here as to which combination of metrics, or models, would be appropriate to provide insight into the ecological condition for a given biome, ecoregion or landscape, we provide two cases studies as examples of the approach (See Page 88). We expect this area of research to develop and refine as geospatial ESG methods are developed and as in-situ data products improve.

Figure 34 – Simple data-agnostic approach to standardising how we assess ecosystem and biodiversity impact for a specific asset, capturing original baseline values for historic and recent years and allowing comparison to recent changes detected via remote sensing satellites. We are, of course, not attempting to list specific direct or indirect metrics for asset classes but rather taking the approach of dividing the topic, via time, impact type and spatial dimension.

- Direct and Indirect Impact/s** – Here we have divided these impacts to align to the ex-situ data reality, where it is frequently more technical possible to capture direct impact, from ex-situ data. While of course indirect impacts, such as heavy metal pollution, have significant consequence on ecosystem condition, many cannot be captured well or at all by ex-situ technologies – suggesting the need for a wide range of data products and solutions to provide estimated, modelled or in-situ insight.

No data solution can solve the biodiversity puzzle alone. Geospatial ESG approaches cannot provide insight into all aspects or highly granular detail into specific components of ecosystem condition. However, they do provide a highly valuable additional lens that can be combined with other data approaches to add to other ESG approaches.
- Infrastructure and Supply Chains** – To keep things simple for now, we have not included supply chain and route transportation metrics within the framework, but essentially, each supply chain asset is assessed in the same way as any other asset (See Page 78). Route planning remains an area for further research, where it is not yet clear how to address shipping and aviation routes; this is reliant, in part, on what supply chain data become available.
- Data- and Model-Agnostic** – As stressed throughout this document, this approach is entirely data- and model-agnostic. Only a consistent framework is required: here we propose the use of the same entity identifiers, baselines and environmental context; the same area delineations (IBLG); the distinction between direct and indirect (destructive and reductive) impacts; etc.

Here we describe these concepts as a starting point, to aid discussion and debate. It should be noted that from a conservation science perspective, there are technical inconsistencies and issues in the insights generated via such an approach. However, it is important to consider these shortfalls in the light of the application, and ask whether such methods, despite their limitations, offer improved value to the financial sector.

In the next section, we explore the issue of quantifying biodiversity and ecosystem impact insights.

PART 5

QUANTIFYING BIODIVERSITY AND ECOSYSTEM IMPACT

KEY POINTS

- A single unit of measurement is often considered desirable for 'biodiversity' or 'nature-related' impact as it simplifies understanding. Within the climate space, the unit used is often a ton of carbon, a fixed unit of measurement to which any GHG emission issue can be converted.
- Within the biodiversity space there is no straightforward equivalent – there is no ton or inch of 'biodiversity'. Despite this there have been efforts to produce a single measurement unit to define 'biodiversity' impact.
- For nature-related geospatial ESG insight, we suggest that the advantage in doing so is heavily outweighed by the technical difficulty, the large potential for error it creates and confusion around what the value reports.
- Instead, we recommend reporting direct measurements for any given metric, applying peer-to-peer comparison.
- Since geospatial ESG methods are able to consistently screen the assets of entire sectors, we suggest using percentiles, direct or adjusted to landscape condition, and/or biodiversity values (e.g. rarity, richness) or user weighted values as a simple means to compare assets or companies across differing metrics. This enables the simple identification of which companies have multiple assets flagged within extremely high or low percentiles for any given set of metrics.
- As touched upon throughout the paper, the impact of any given asset varies with the current resilience of the ecosystem. Here we outline in detail how the magnitude of IBLG impacts can potentially be adjusted to Landscape condition insight. These weighted adjustments can of course be applied within peer-to-peer comparisons.

QUANTIFYING BIODIVERSITY AND ECOSYSTEM IMPACT

Across insight into ‘biodiversity’ and ‘ecosystem condition’ in general, a range of measurement units will be reported capturing differing variables. Frequently this will be an area value (e.g. km²), but it can also be categorical (e.g. ecosystem type, species rarity), a range of statistics (e.g. mean, min, max, STD, etc..) and in different units (km, kg, PPM, etc.).

The question that arises is how to convert these values into quantifiable comparable units of ‘ecosystem condition’ and or ‘biodiversity’ values. Within the climate change data arena, the issue is simple: it is possible to covert or report results in universal accepted quantified units, (e.g. a ton of carbon). Within the biodiversity space the issue is less straightforward – there is no inch, kilogram or ton of ecosystem or ‘biodiversity’. We cannot talk of 5.5 ‘tons of ecosystem lost’.

There is an increasing body of work which has and is attempting to create “biodiversity measurement units”. For example, the UK government is working towards developing a ‘Biodiversity Metric’¹²⁶ designed to calculate, with in-situ data, the biodiversity net gain within given areas as required under the 2021 Environment Act and within future legislation, giving a site baseline and forecast future biodiversity values.

More broadly, other efforts could be considered as attempts to move towards a systematic unit for measurement for ‘biodiversity’, for example:

- **Mean Species Abundance (MSA)** is a measure of the current abundance of species relative to their abundance in the equivalent undisturbed ecosystem. Ranging from 0 and 1, higher scores suggest greater local biodiversity intactness. Derived from the GLOBIO model,¹²⁷ it is an accumulated function of six human pressures (land use, road disturbance, fragmentation, hunting, atmospheric nitrogen deposition and climate change); the core model considers pressure–impact relationships.
- **Potentially Disappeared Fraction of Species (PDF)** is a measure of the percentage of species lost in 1 m² (land) or 1 m³ (water) in one year in a specific area due to environmental pressures. It is derived from the ReciPe model, originated from the pharmaceutical sector – where the potential environmental toxicity of a substance is expressed as a fraction of the species that potentially disappears when the substance is introduced into a given environment.

Within geospatial ESG applications, it’s important to consider the technical challenges in converting impact into a biodiversity or ecosystem impact against the advantages in doing so for the common ESG use cases.

	Impact	Ex-Situ Metric Available?	Unit of Measurement	Conversion to Biodiversity / Ecosystem Impact	
Direct Impact/s	1. Forest Loss		Sq KM	(?)	Peer to Peer Ratios/ Comparison
	2. Grassland Loss		Sq KM		
	3. Etc...				
Indirect Impact/s	1. Freshwater use (Groundwater)		Liters	(?)	
	2. Light Pollution		Candela per Sq M		
	3. Noise Pollution		Deci Bels (dB)		
	4. Water Pollution (Chemical)		PPM		
	5. Water Pollution (Heavy Metals)		PPM		
	6. Air Pollution (PM2.5)		PPM		
	7. Air Pollution (PM10)		PPM		
	8. Air Pollution (VOCs)		PPM		
	9. GHG Emissions (CO2)		PPM		
	10. GHG Emissions (CH4)		PPM		
	11. Fertilizer (Nitrogen) Runoff		Kg/Ha / PPM		
12. Soil Contamination (Lead)		µg/g (micrograms per gram), mg/kg, or ppm (parts per million)			
13. Invasive Species		?			
14. Etc...					

Figure 35 – Table illustrating the challenges in converting differing units of measurement into a consistent quantified ‘biodiversity/ecosystem unit’

In this section, we will look at the trade-offs in quantification, and suggest potential solutions.

DIRECT IMPACTS

Direct impacts are initially simple to quantify in a consistent unit of measurement: the area of environmental asset lost, relative to spatial footprint (e.g. per km²) or production (e.g. per ton). These can be additionally expressed, if desired or useful, as ratios (against remaining habitat with the landscape, ecoregion), trends over time, etc.

Many actors will wish to adjust direct impact results to factor in the importance of other variables, such as biodiversity richness, endangered species, etc. Such value adjustments, defining which environmental assets are more ‘important’ than an equal area of another, move into the subjective. Since the geospatial ESG approach is data- and model-agnostic, third parties can develop any weighting or adjustment required.

INDIRECT IMPACTS

Indirect impacts are more varied and complex to quantify, covering a huge range of variables and units of measurement, which are difficult conceptually to factor – what, for example, does it mean if 10ha of forestry plantation is cut down in one part of the world and 1,000 litres of groundwater extracted in another? What was each’s ‘biodiversity’ and ecosystem impact, and how can we combine hundreds of such measures across vastly differing ecosystems?

Considering current methodological limits, it is arguably more practical, understandable and accurate to simply compare measurements peer to peer – adjusting for location, ecoregion, spatial size or production of the asset – than to attempt to translate these results directly into terms of ‘biodiversity units’. However, because different sectors will need to use differing metrics, (e.g. oil and gas can be assessed for marine oil spills; cotton farming cannot), it is necessary to find a means to compare differing metrics. Otherwise, it will become difficult to compare companies from different sectors which have limited overlap in the metrics applied (e.g. a clothing brand vs. a mining company).

Since, via the geospatial approach, we can (asset data dependent) assess all assets within a sector, it is possible to determine the percentile range for each metric directly and adjusted (Figure 36). For example, which palm oil plantation is within the 99th percentile for deforestation per km² within the last five years? Or which real estate assets cleared more than average biomass values per km², adjusted for ecoregion ‘biodiversity richness’.

Company X	Metric 1 – Habitat Loss per km ² Percentile	Metric 2 – Habitat Loss per km ² Percentile Adjusted for Ecoregion Richness	Etc.
Mine 1	50.5	46.4	
Mine 2	45.6	38.1	
Mine 3	88.2	99.2	
...			

Figure 36 – Illustration of metrics for a mining company tracking its three mines, reporting their relative percentile compared to all other mines.

The advantage of percentiles is that they help inform which assets are outliers compared to their peers, in a format which can be consistently compared again any other metric. Again, metrics can be adjusted to account for biome richness, social variables, production, spatial footprint, etc. Additionally, ‘red flags’ (0/1) can be assigned for compliance breaks, such as if the asset is operating within ‘no go’ sites or sites of extreme value (e.g. World Heritage Site).

It is important to note that the approach of geospatial ESG outlined here is data- and model-agnostic. More intelligent models – spatiotemporal spheres of influence – can be built around these inputs, to adjust for ecoregion sensitivity, biodiversity richness and landscape ecological condition. Or if the data and science develop, models can be produced which include a translation into a single ‘biodiversity’ unit. However, in the short-term, we’d argue, the simple method of direct peer-to-peer comparison is a viable solution.

FACTORING IN 'LANDSCAPE' RESILIENCE

It is, of course, necessary to adjust results to account for simple variables, such as the spatial footprint of the asset, production volumes, regional biodiversity richness, etc. It is also vital, however, to apply the data available in ways which maximize insight – and importantly to find ways to adjust the weighted magnitude of localized impacts to account for the changing resilience of environmental assets present across the landscape.

Here we look in detail at the concept of using Landscapes (L) – we suggest water basins – to provide improved insight into metrics which are not possible at granular scale and to define landscape condition/resilience, which can then be used to weight/adjust IB impacts.

This approach serves four important functions:

- Often within small areas, such as within property boundaries, many indirect impacts are difficult to measure via ex-situ SRS solutions but can be estimated across larger areas.
- For example, mercury pollution within a given tributary or area of the Amazon can be estimated by tracking via SRS the number of mining barges and the changing extent under illegal mining operations.¹²⁸
- Landscape-wide environmental extent and condition indicators are likely to be useful to adjust the magnitude of localized impacts. For example, if the extent of native forest cover within a landscape dramatically reduces (90% loss), then the resilience and the significance of any impact to any small areas of forest within a property boundary within that landscape also changes.
- Ecosystems are large and often interact with hundreds or thousands of assets. To avoid issues around the tragedy of the commons and incentivize all actors to address issues within their landscapes of operation, the indicators describing the overall health of the landscape need to be assigned to all actors. This will place greater attention on poorly performing actors, as ultimately, in the long run, irresponsible actors are likely to cost society and the economy.
- When asset data or exact supplier is unavailable, often it is possible to locate the supplier or asset to a country, state, municipality, etc. An area-based metric derived from landscape methods and/or scores can then provide insight into a very approximate likelihood of environmental impact.

Before we look in detail at two potential examples of landscape indicators – river environmental flows and forest temporal autocorrelation – we first explore why this is needed.

THE RATIONALE FOR LANDSCAPE INSIGHT FOR IB IMPACT ADJUSTMENT

The Great Auk was once common across the north Atlantic coastline; flightless and vulnerable, they were hunted for their down, then as their rarity increased for their skins and eggs for collections. Their populations plummeted from the 16th to the 18th century. The last pair found were killed on 3rd July 1844, on the request of a merchant who wanted the rare bird skins to sell for collections.¹²⁹ History records the names of the men who killed, if not the last, but some of the very last Great Auks.

The Great Auk extinction has a parallel for us now, in understanding landscape impact. The final blow, the *coup de grâce*, the final loss of a section of habitat or a species, is dramatic. It gets our attention and our blame. It tugs at the heart. But of course, it would be foolish to blame the extinction of a once-widespread species on a few men and one action. The extinction was caused by endless repeated actions by tens of thousands of individuals over hundreds of years. And so it is with all impacts to the natural world. In a healthy landscape, with robust ecosystems, minor impacts are likely to be absorbed and recovered from without issue. As impacts continue and mount, as habitat declines, each additional impact becomes harder to reverse and recover from, until a tipping point is reached, and recovery is impossible (Figure 37).

As with the Great Auk, initially impacts can be absorbed; but as impacts continue, resilience decreases within the ecosystem (or species), and the magnitude of the impact increases as recovery becomes less and less certain, until collapse is certain (Figure 37).

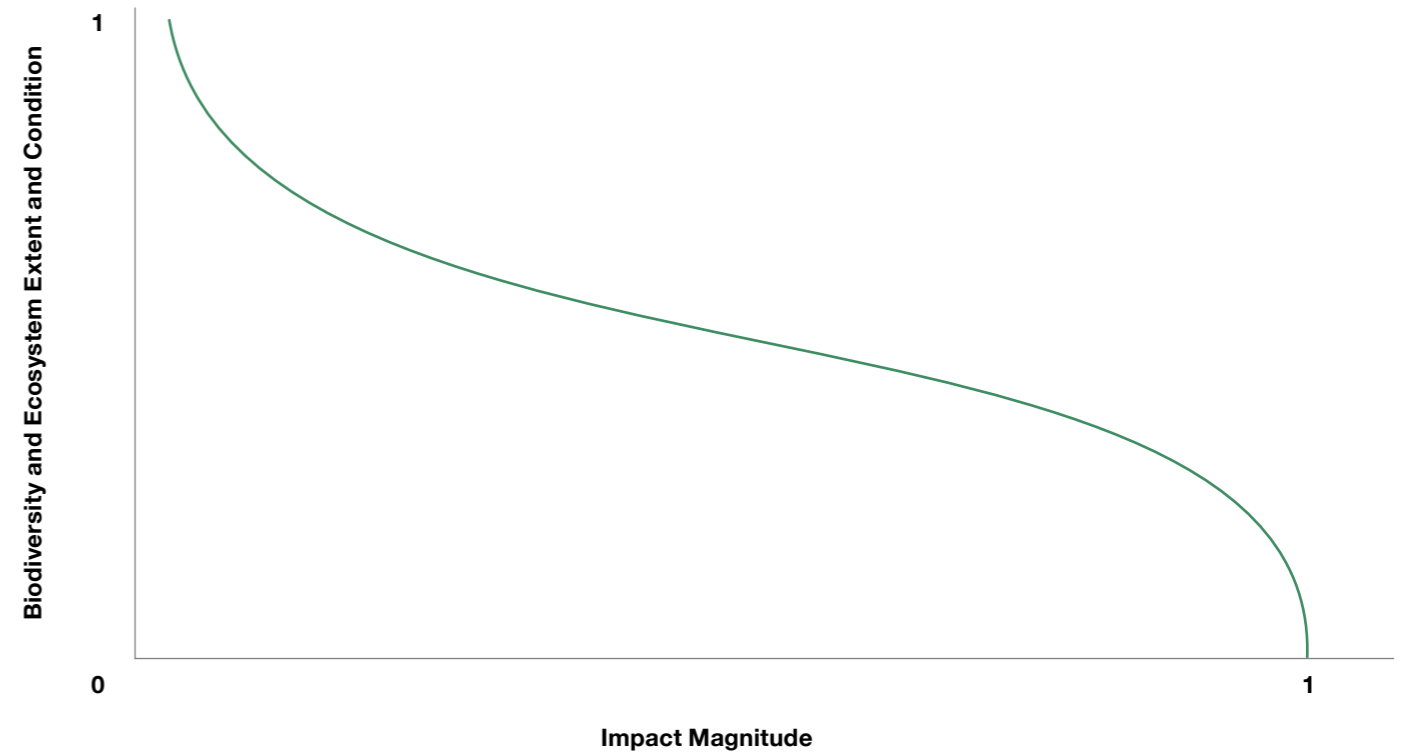


Figure 37 – Simple graphic illustrating the concept that impact is not a fixed value but changes in magnitude according to biodiversity and ecosystem condition/resilience. The green line is species, ecosystem, impact, temporal, etc., specific and will vary in form to each unique situation.



The localized, regional, global and cumulative impacts of an asset then are not static values but change with the condition of the biodiversity and ecosystem present. As biodiversity and ecosystem health decrease, due to impact within a landscape, its ability to recover reduces, and a point is reached where degradation and loss are higher than recovery and, if continued, will force the ecosystem into collapse. As a proxy measure, we propose to use water basins¹³⁰ (See Page 88) to provide wider 'landscape insight' to adjust the IB impact weighting of assets to approximately account to changes in resiliency.

Photo: Great Auks, birds which were once common, are now extinct, changing the arrangements of cogs within the marine ecosystems they were once a factor within.

Specimen No. 8 and replica egg in the Kelvingrove Art Gallery and Museum, Glasgow.

LANDSCAPE METRICS

On Page 24, we discussed using ex-situ data to provide insight into ecosystem condition, noting that it is extremely challenging and almost always necessary to us in-situ data to aid insight. Further, we noted that there is no widely agreed method for measuring the ecosystem, or ‘landscape ecological integrity’ of related areas with ex-situ data alone. Consequently, the question for geospatial ESG then, is what if any insights could be gained on estimating ‘landscape condition’?

If we accept that we cannot easily define ‘ecosystem condition’ via ex-situ data alone at this time, we can nevertheless look at what proxy indicators we could use that might be accurate enough for geospatial ESG applications.

One potential way forward is to select a key set of natural assets within a landscape (e.g. forests, rivers, wetlands) and develop methods of estimating their condition, at a high-level, where it might be possible to triangulate observational datasets together to give rough insight (Figure 38). Of course, it is important to state that it is necessary to develop indicators of both global and regional application, as in many cases it will be necessary for tailored solutions to provide insight specific to ecosystems and impacts not found elsewhere (e.g. global forest loss and regional mercury pollution in the Amazon).

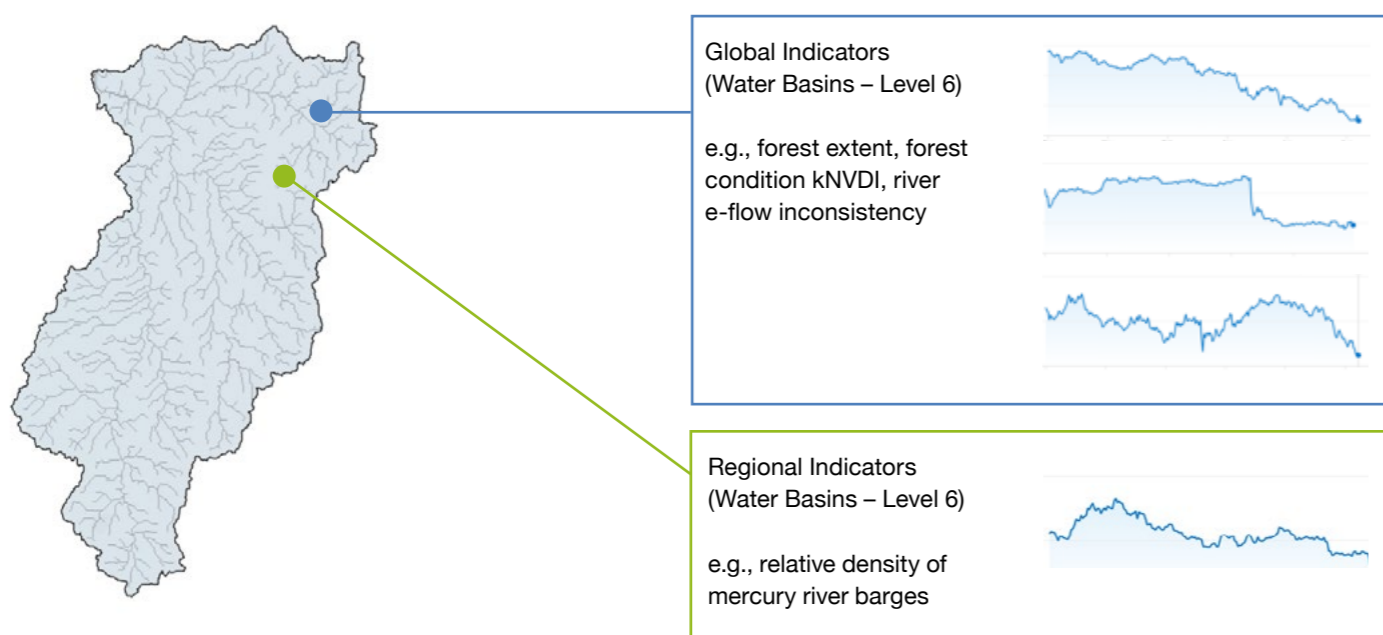


Figure 38 – The concept of area-consistent landscape level ‘indicators’ produced **regularly and consistently** week on week, **month on month** tracking back to the 1980s to provide insight on what is occurring within each water basin. This is vital for 1) wider proxy measures of impacts difficult to measure at the fine scale, 2) situational context to adjust the magnitude of IB impact and 3) to attempt to address issues around the tragedy of the commons.

On the next pages, we explore two such examples; however, caution needs to be applied, as while in most cases these metrics are likely to provide some form of useful estimation, further research is required to refine benchmarks and iterate these approaches (e.g. metric correlation to ecological processes, addressing sampling errors, quantifying relationships and transferability of metrics, etc.) in order to know what exactly these outputs are reporting and the various complications. Interestingly as the field of geospatial ESG develops, with increased research focus and access to emerging data and technologies (e.g. eDNA, landscape audio) and improved in-situ data aggregation and management, it seems inevitable that progress will be made on landscape condition insight. And indeed, ongoing research, such as GEO BON Essential Biodiversity Variables, is making progress.

Indeed, it seems likely, as the climate and biodiversity challenges deepen, that we will move into ‘landscape data catalogue’ metrics/statistics being reported as critical data points, across tens of indicators at high frequency (weekly, monthly), as we see now with key economic data points like GDP. For now, it is important to highlight this issue as a vital area for research and development.

In the next section, we look at two examples of potential estimates of landscape condition.

RIVER CONDITION AS A PROXY MEASURE FOR DEFINING LANDSCAPE CONDITION

Authors: David Tickner, Chief Adviser, Rivers – WWF-UK and Conor Linstead, Freshwater Specialist – WWF-UK

Rivers and related freshwater habitats such as lakes and wetlands host globally important biodiversity, including charismatic species such as otters and river dolphins, a wide array of specialist plants and invertebrates, and more fish species than are found in the oceans. This biodiversity is vanishing more than twice as fast as the biodiversity on land or in the sea.¹³¹ In response, scientists and campaigners have set out an Emergency Recovery Plan for freshwater biodiversity.¹³² As well as helping financial institutions to understand risks associated with their investments, better global-scale monitoring – combined with monitoring at national, river-basin and local scales – can help to track progress in implementing this Plan.

Threats to river health and biodiversity include alteration of river flows through abstraction of water for agricultural, industrial and domestic uses; pollution from a wide array of sources; invasive species; construction of dams and levees; over-fishing; and riverine mining of sand and gravel for the construction sector. Such threats can impact on biodiversity individually and cumulatively through multiple stressor effects. Changes in rainfall patterns and water temperatures due to climate change are increasingly a concern.

Rivers are also key biophysical features linking landscapes and connecting terrestrial habitats with coasts and oceans. Many of the threats to biodiversity in rivers are driven at least partly by changes in land use. Thus, data on river health can provide clues to wider landscape condition.

River health data is often classified into water quantity/hydrology, water quality, physical habitat and biological variables. Water quantity variables describe alteration of natural hydrological flow regimes (i.e. the extent to which natural spatial and temporal patterns of river flows have been anthropogenically changed) and changes in water extent, e.g. in floodplain wetlands. Water quality parameters include water temperature, dissolved oxygen, biochemical oxygen demand (BOD, an indicator of microbial activity) and pollutants such as nutrients (e.g. nitrogen and phosphorous), suspended sediments, heavy metals and synthetic toxicants. Physical habitat includes longitudinal (upstream-downstream) and lateral (river-floodplain) connectivity, physical features within rivers (e.g. islands, sandbars) and aquatic or riparian vegetation. Biological variables include macroinvertebrate diversity and abundance (a proxy for water quality), fish, non-native invasive species and primary productivity.

Several national and regional river programmes that combine in-situ, ex-situ and modelling approaches have been developed in recent years¹³³ but currently there are challenges to effective, harmonized global-scale river health monitoring. Conceptually, the fact that rivers are essentially linear, flowing features means that indicators that track on river habitat quality by length or volume would be better than conventional area-based monitoring and metrics that are commonly used by the global conservation community.

The narrow dimensions of small to medium-sized streams (which comprise much of the global river network), variability of river flows, and the physical properties of water also mean that SRS technologies have struggled to accurately monitor changes in flow regime or water levels at sufficient spatial and temporal resolution. However, initiatives such as the Surface Water and Ocean Topography (SWOT) project¹³⁴ are likely to improve the situation, at least for larger rivers.

One indicator that can currently track global changes in river health effectively is the Connectivity Status Index.¹³⁵ The CSI considers five ‘pressure factors’ that represent the main human alterations to river connectivity: a) river fragmentation; b) flow regulation; c) sediment trapping; d) water consumption; and e) infrastructure development in riparian areas and floodplains. Proxy indicators for these components were informed by available global data and numerical model outputs and combined using a weighted overlay model. The CSI has been used for a number of purposes, including to map remaining free-flowing rivers worldwide and to assess the overlaps between protected areas and dam construction.¹³⁶

Researchers are now developing pathways for improving global scale monitoring that build on lessons from national and regional schemes and indicators such as the CSI¹³⁷ and recent initiatives such as Global Water Watch¹³⁸, funded by Google, are aiming to make available high resolution, near-real-time water data using AI technologies. Global-scale monitoring approaches will inevitably rely significantly on ex-situ approaches for the foreseeable future and technological advancements promise better tracking of changes in water quantity, water quality and physical habitat. Monitoring of biological indicators using SRS technologies is intrinsically difficult, with the exception of primary productivity, for which chlorophyll can be used as a limited proxy. However, scientists have begun to assemble global-scale data of biological variables from in-situ datasets¹³⁹, and it’s possible that these could be combined with SRS data to provide better geospatial coverage.

From a landscape conservation and river health perspective, one particular need is to develop global monitoring of river flows. In many contexts, flows naturally change on a frequent – sometimes daily – basis. Anthropogenic changes to land use and infrastructure operations (e.g. flow releases from dams) have greatly affected such natural flow variation, normally to the detriment of aquatic ecosystems and biodiversity. A combination of ensemble modelling of natural or pre-industrial baseline flow regimes and near-real-time flow data (from SWOT data, for instance) could provide a global picture of human impacts on river flows. This could serve multiple purposes including risk assessments for financial investments in river basins that might be vulnerable to unsustainable water use.

FOREST CONDITION AS A PROXY MEASUREMENT FOR DEFINING LANDSCAPE CONDITION

Forests can be analysed to provide insight into their own condition but also potentially insight into the wider landscape condition, where the sudden and rapid expansion of forest clearance, increases in artisanal mining, etc., is perhaps indicative of some other social or economic change.

SRS, with the growth of optical, radar, lidar and high cadence data, has come a long way in recent decades in linking satellite data (spectral values) to ground truth data, to accurately quantify changes in forest characteristics (e.g. leaf area index, phenology, biomass, canopy gap fraction, taxonomic diversity, etc.) across the globe and over time.

This research has potential application within geospatial ESG, as we attempt to understand forest ecology and condition at scale. At the most basic level, we can define via SRS outputs, the extent of the forest and any forest gain or loss, week by week. We can apply more complex methods for improved insight, for example understanding the native, non-native, primary or secondary forest, or other variables.

To illustrate just one area of potential interest, researchers are exploring the concept of 'forest resilience indicators', methods to identify early indications of regime shifts. For example, Forzieri et al.¹⁴⁰ have shown that tropical, arid and temperate forests (both managed and intact forests) are declining in resilience. Only the northern boreal forests seem to be bucking the trend, perhaps from a warmer climate and CO₂ fertilization. The global consistency, with 23% of intact forest worldwide reported to have reached critical threshold of resilience, suggests the large-scale driver of climate change.

Reduction in resilience is known to be linked to sudden declines in forest primary productivity. Lower resilience within a landscape suggests a lower capacity to overcome additional impacts and therefore an increase in the magnitude of any IB forest impacts.

When an ecosystem begins to fail, it has been proposed that a loss in resilience can be detected from an increased temporal autocorrelation (TAC), reflecting a decline in the system's ability to recover due to a critical slowing down (CSD) of system processes. Forzieri et al. estimated global forest CSD from a 1-lag TAC from SRS product kernel normalized difference vegetation index (kNVDI) as a proxy for ecosystem productivity. They compared the kNVDI in a three-year rolling window from 2000 to 2020, using a random forest regression model to filter out localized environmental factors, which might otherwise hide the resilience signal (Figure 39).

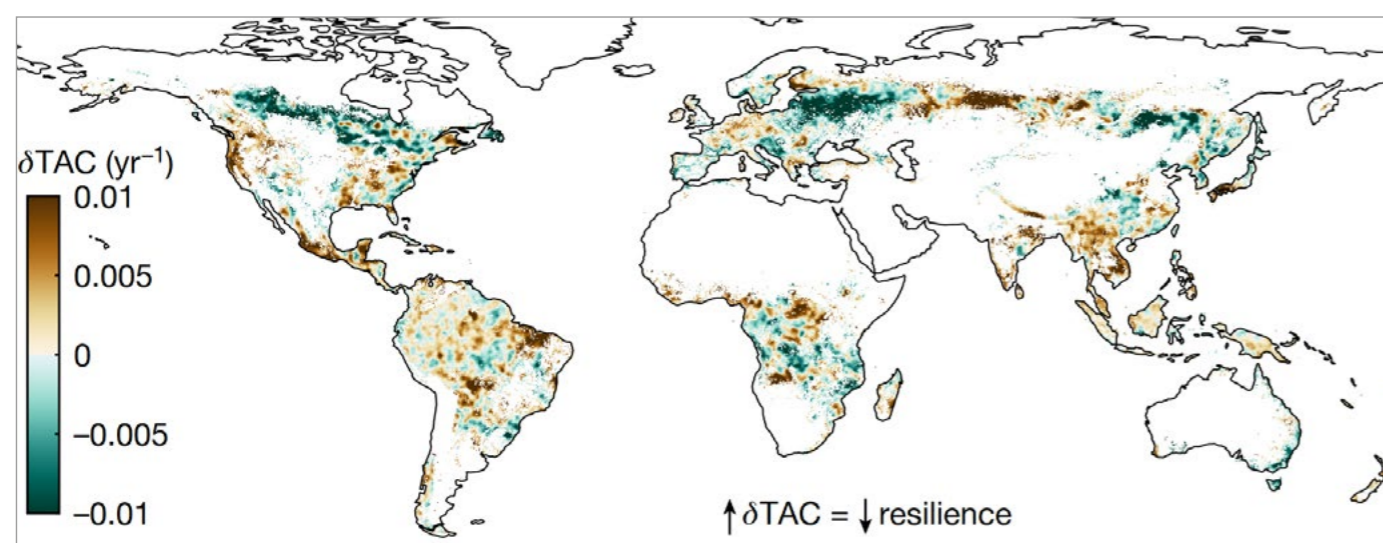


Figure 39 – From Forzieri et al., 2022: global map of the temporal trend of TAC (δTAC); positive δTAC values imply a reduction in recovery rates and thus a decline in resilience, and vice versa for negative δTAC values. Such research suggests a possible way forward for developing landscape-scale forest resilience and condition insights.

Further research will be required to better understand the viability of outputs for geospatial ESG application. Arguably, however, this study is illustrative of the wider efforts within the remote sensing communities that are taking us closer to improved data products, capable of supporting geospatial ESG landscape condition indicators.

A key development will be for the SRS community to realize that their outputs could be of significant value and application to the financial sector, if designed for purpose and arranged in a universally consistent format, applicable across geospatial ESG-driven methods and models. Here we suggest producing landscape metrics for water basins (See Page 68).

REFLECTIONS ON QUANTIFYING BIODIVERSITY AND ECOSYSTEM IMPACT

There is a temptation to be dissatisfied with the above – that it doesn't quite get to the heart of the question. It doesn't define in one single unit the 'biodiversity' impact of any given asset, or company or portfolio. Instead, it provides proxy insights such as an asset's association with habitat clearance, and effectively unrelated 'environmental impact variables' such as light pollution. It gives insight into 'impact' variables and less into actual 'biodiversity and ecosystem condition'.

The reality is that with the field just emerging, there is – as of yet – no clear ex-situ geospatially focused methodology as to how to define 'ecosystem and biodiversity' impact for any given asset class or within any given ecosystem. As time goes on, we'd argue that the framework outlined allows the improved integration of in-situ data to allow more refined models exploring ecosystem condition and getting more into the granular detail of 'biodiversity'.

However, let us reflect on that fact, that if we were able to do the very basics proposed here – defining every asset on Earth and its ownership, and links via supply chains within the economy, and applying observation data to provide insight into direct and indirect impacts – **we would know significantly more than we currently do.** We would know for the first time which assets were within or nearby to habitat clearance. We would know every company on earth that is engaged directly or via supply chains with assets impacting high value environmental assets, or legally designated areas. We'd have a nearly complete understanding of which supply chains were deforestation free and which weren't. The list goes on and on. This would be a significant quantum leap forward in our current understanding. Of course, it would not provide a direct answer as to the true 'biodiversity' impact of these assets, factoring in cascading issues and hundreds of other complexities – but vitally, it begins to build a means, a framework and the data to get us closer to that objective, while still producing useful insight.

The reality of our position is that within the next 12–24 months, no single team or even wide collaboration is going to resolve how to estimate for every given asset its actual ecosystem and biodiversity impact with ex-situ data alone. However, by pursuing the field – by normalizing and establishing the field; by setting out observational datasets, metrics and the approach; by building out a systematic data catalogue; by testing and building landscape condition methods – we will in time position ourselves to provide these more detailed answers. In short, we argue that instead of building more one-off platforms or solutions, we should apply the data available now to build the foundations of the approach. Building a robust data ecosystem will enable the development of a new sector of open and propriety third-party models and tools catalysing the field and leading to commercially applicable solutions (See Page 98).

In the next section we explore how we might go about building the emerging field's foundations, to produce and iterate 'biodiversity and ecosystem' insights.

PART 6

MOVING FORWARD

KEY POINTS

- The current approach to biodiversity insight is user driven – a single flashlight in an ocean of darkness. Only when an FI focusses (via a specific standalone tool) on a specific asset or company does any insight come to light. The rest of the equation, the impact of other 99.99% of companies and their supply chains, however, remain in darkness.
- Adapting and reusing the same approaches of the past, reshuffling the same isolated data and platforms, will not solve the biodiversity puzzle. We need a new approach to light up every asset, every company at once without the user driving the equation.
- We are under pressure to generate solutions if we are to influence the biodiversity and climate challenges. Solutions need to be online within the next 24 months.
- One potential way forward, following developments in the climate space, is the establishment of a data commons. This would improve data access, potentially across all relevant domains, and importantly means uniting and iterating data models and solutions within the community – to help ensure solutions are not lost in siloed efforts.
- Specifically, we suggest that resolving access to asset and supply chain data will not be achieved via current open or commercial initiatives. Here we suggest the need for an ‘asset registry’ within the data commons, with a clear mandated, funded and tasked actor who is made responsible for resolving data gaps – promoting a structure where incentives are placed onto the corporates themselves to maintain their own asset data.
- We argue that supply chain data, as highly sensitive data, will pragmatically never be ‘openly available’. We consider that the potential is to design standards and the technical systems within the data commons to allow the secure transfer of supply chain data between corporates and specific FIs for assessment.

MOVING FORWARD

Capitalism has lifted humanity into the modern age; it has helped provide a better life for billions of people. It is also now pushing us towards a less biodiverse, poorer world.

On Page 38, we raise the concept of the extinction economy, the components of the economy on the very edge that quietly burn, taking us closer to global biodiversity collapse. Often this means the clearance of critical, high-biodiversity-value habitat. Such impacts are normally found at the fringe of our economy, but via supply chains flow up into its heart. For example, vast acreages of the Amazon Forest have been and continue to be legally and illegally burnt, converted to grassland for cattle, then later used for soya, supporting a vast legal economy. Facing global biodiversity collapse, the drive and incentive enabling such habitat loss must be minimized. For the financial sector, this means providing transparency on the nature-related history of these assets, and who is buying from these assets.

Of course, there are many complications, and indirect impacts must also be factored in.

If we are to provide such transparency and help stamp out the worst of the fire, we must accept that the current efforts of primarily reshuffling and repackaging the same or very similar 'biodiversity' data or methods of the past to produce 'new' isolated products do not scale to provide robust insight into the ecosystem and biodiversity impact of 99%+ of companies (and their supply chains).

Instead, radically new approaches, significant investment, engagement and commitment from a diverse range of actors will be required. Here we have considered one approach, a geospatially driven solution, which we consider has merit to integrate and support the current data ecosystem (Figure 40).

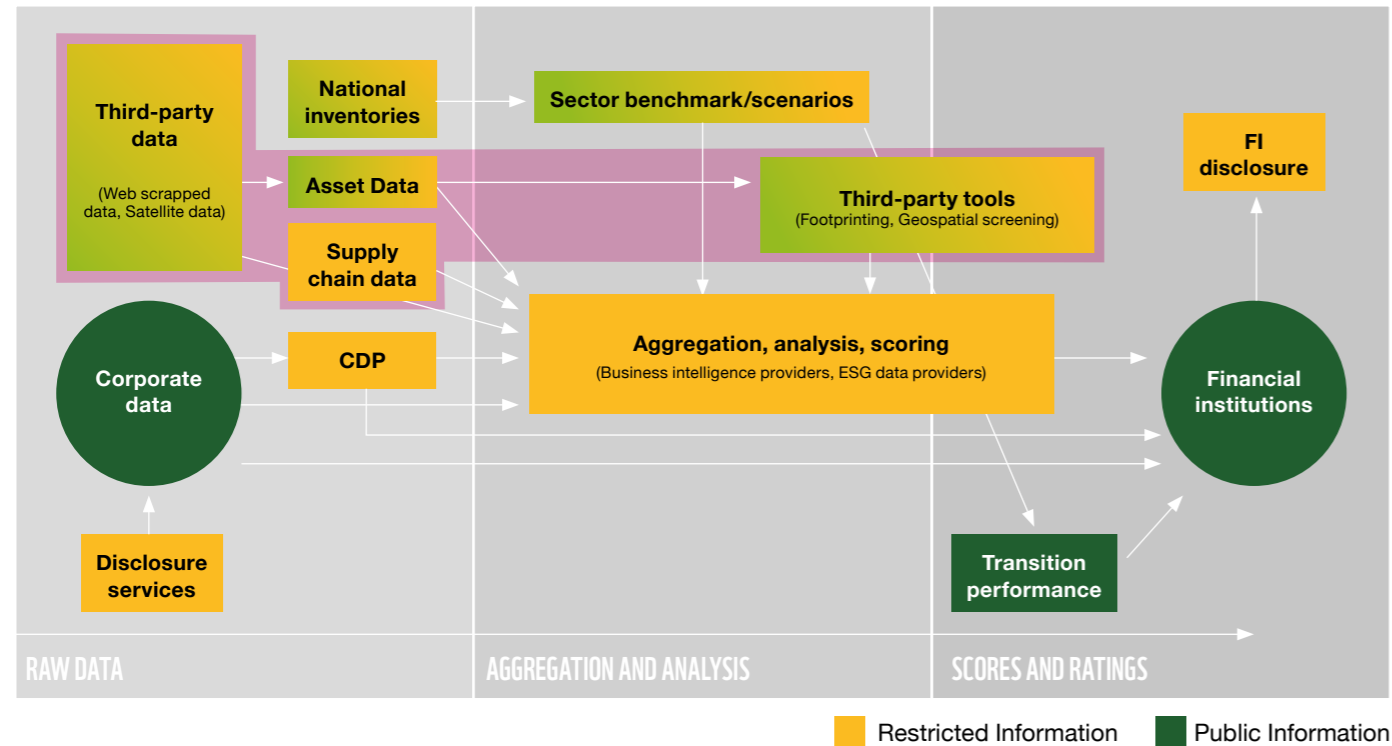


Figure 40 – Diagram, adapted from Climate Arc, 2022,¹⁴¹ highlighting the 'biodiversity' areas of the climate/biodiversity data ecosystem that could be radically improved.

It is likely that the increasing volumes of Earth Observation data, remote sensing methods, rapidly improving machine learning techniques and increasing pressure of society to understand climate and biodiversity will, **in time**, conspire to lead to improved opportunities for insight into the nature-related performance of assets, companies and portfolios. However, we cannot afford to wait.

The reason is simple: it's commonly reported that we have a decade to address the climate and biodiversity challenges. Regardless, we know that nature and climate recovery will be easier, the quicker the response. We know that greater transparency and accountability on who is impacting the natural world aids real world change. Consequently, the sooner functional solutions are online, the better, ideally within the next 24 months.

The question that we now face then is, can we get solutions online fast enough?

Will we be in a position in 2024 where Bloomberg, S&P Global, Refinitiv, etc. and the mainstream ESG data providers are able to offer accurate, independent, geospatially derived data points on the environmental and ecosystem and biodiversity impact for every asset, company, region and nation – including supply chains – week on week? Monitoring across a dozen indicators the 'landscape condition' of every water basin, consistently week on week?

WHAT SHOULD WE DO?

First, it's important to openly acknowledge that there is a problem – that the current status quo does not provide insight at a useful level of detail: the ongoing proliferation of more siloed third-party tools and platforms do not appear to have the reach to radically improve current levels of insight into companies or portfolios. Effectively, it seems unlikely that more of the same is going to help.¹⁴²

Instead, we should explore what might. Here we suggest that a key part of the solution lies in a geospatial driven data approach and in working together – not apart.

To illustrate this, consider what a business intelligence provider would need to single-handedly deliver global insight into biodiversity and ecosystem impact as outlined in this document? They'd need, roughly speaking;

- Asset data for every asset on Earth
- Dynamic supply chain data for every company
- High resolution and high cadence SRS data
- SRS capacity and the means to develop metrics/observational data from SRS data
- Cloud compute to process SRS data and generate GIS insight
- Ecosystem and biodiversity data
- Ecosystem and biodiversity asset/sector specific impact methodologies
- Landscape condition methodologies/insight

It is effectively impossible for any single actor to pull together the above; it crosses too many highly specific domains. For sake of argument, a major business intelligence provider is unlikely to one day find itself in the position of having more biodiversity and ecosystem data, field access and engagement, and understanding and influence on ecological integrity concepts than the conservation sector. Nor is it likely to achieve more technical SRS capacity than the SRS sector.

Rather than each business intelligence provider, or even FI¹⁴³, trying to do this independently – source its own asset datasets, its own supply chain data, its own ecosystem for SRS data, its own connections with the NGOs and IGOs to gain access and influence on ecosystem and biodiversity data and methods – we can build a data commons which allows anyone to benefit from the work already generated. It is far more practical for us to build interoperable systems, with clear open/propriety structures, to allow actors to securely pull the data resources they need, iteratively develop and refine models together – than for each of us to try to secure the same data and develop the same methods separately.

In short, we need connected platforms of platforms – we need a data commons, where we can unite data, and crucially share and iterate methodologies, models and code. And for that, we argue, it makes sense to establish an international independent 'centre', responsible for key deliverables, as without an actor having mandated responsibility, it seems unlikely that the public good aspects of the equation will be resolved.

DATA COMMONS

A data commons unifies a wide range of data to make it more accessible and useful. For this application, this effectively means the provision of the necessary data infrastructure, protocols, standards and security to enable actors to openly or behind paywalls share asset, supply chain and observational datasets between themselves. On top of this, specific ex-situ biodiversity and ecosystem models and methodologies can be made openly available to allow actors to together test, benchmark and **iterate solutions**. Furthermore, an ‘app-store’ of third-party commercial solutions can be made available, providing FIs with all levels of access, from raw data to data models and metrics; or conversely ESG providers can source and develop finalized ESG scores into their systems.

A comparable example comes from Open Source-Climate (OS-C), a non-profit organization which is providing open-source data and software to aid climate-aligned investment.

OS-C DATA COMMONS

Author: Vincent Caldeira, Field CTO APAC at Red Hat & Chair of the Technical Advisory Council at OS-Climate

OS-Climate Data Commons is an open data platform that was designed and built from the outset on a distributed architectural approach for data management in order to address some of the fundamental gaps in climate-related data that hinder financial institutions (including central banks and supervisors), investors and policymakers from assessing financial stability risks, and properly pricing and managing climate-related risks.

We believe these critical gaps, as defined by NGFS in their “Progress report on bridging data gaps”, are applicable to biodiversity data as well:

- **Data availability:** Climate-related data needs to be accessed across asset classes, sectors and geographies, and over different timeframes. Data may not exist, or lack the appropriate granularity and/or geographical and/or sectoral coverage, or may not be easily accessible from a technical perspective. Also, increased volumes of data generated constantly, across a number of heterogeneous systems, makes it difficult to build consolidated views that stay relevant over time.
- **Data comparability:** Data generated by a wide variety of sources with differences in design resulting from the existence of multiple frameworks for climate-related disclosure, as well as lack of consistency in data formats and standards, makes it challenging for end-users to compare data across sources and frameworks.
- **Data reliability:** Reliability depends on the provenance and quality of the raw data, as well as the auditability and transparency of the providers and data processing employed. This information is generally not fully audited and transparent.

OS-Climate Data Commons addresses this through a data platform built on a data mesh architecture and on the foundation of open-source components – integrated and interoperable tools and libraries used every day by data engineers, data scientists and end-users of the data.

There are a number of key principles in adopting and implementing a distributed data mesh, namely:

- OS-Climate Data Commons defines data domains, which provide a crucial first step in identifying where vastly distributed climate data exists and what it contains.
- It identifies owners for data domains, which will empower individuals or groups to define and manage requirements for data discoverability, understandability, quality and security within their domain.
- It implements a ‘self-service’ model, where access to data domains is defined and managed through standard and consistent technical mechanisms provided through an open platform, making it easy for data engineers, data scientists and user organizations to access climate and ESG data without the requirement of complex technical skills to manage the infrastructure and tooling behind the data.
- It also defines and implements a ‘federated’ governance model, which respects local autonomy and agility while also addressing broader OS-Climate organizational and regulatory constraints, as well as enforcing consistent best practices for data management across the organization.

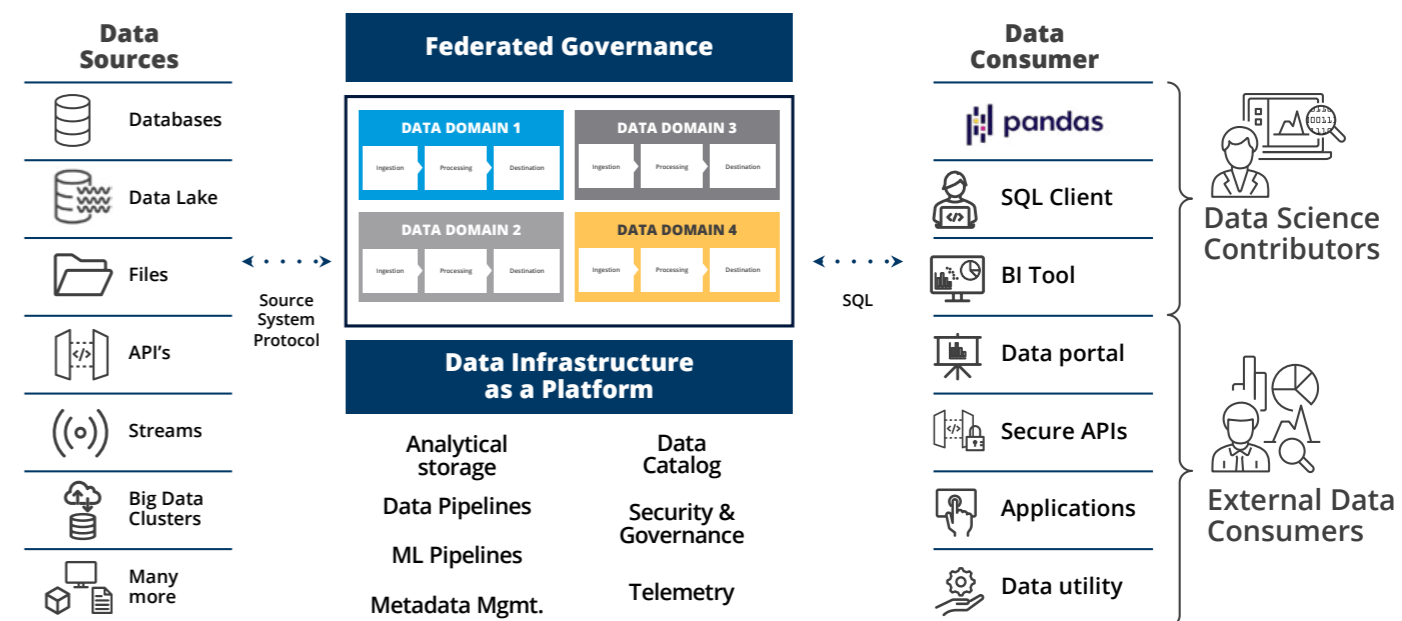


Figure 41 – Overview of OS-Climate Data Commons architecture

It is also important to note that OS-Climate Data Commons, as any implementation of a data mesh, is not a product or a single vendor solution. Rather, it is a composition of components that make it easier to share and distribute data at scale, and a collection of processes and practices adopted by the organization, OS-Climate, to ultimately make climate data easier to find, easy to access, easy to understand and easy to compare. On the technical side, this includes a metadata catalogue that allows discovering data, a query federation service that helps to integrate and build interoperability between different and technically heterogeneous data sources, and a policy engine that supports the formulation and enforcement of data compliance policies across the platform. On the process side, this approach is supported by the establishment of distributed ‘data products’ that have clear boundaries and owners, as well as standard practices of ‘data as code’ across the organization. Data as code is an approach that requires the ability to process, manage, consume and share data in the same way we would typically use for application source code management, allowing full transparency and reproducibility of data integration and processing over time.

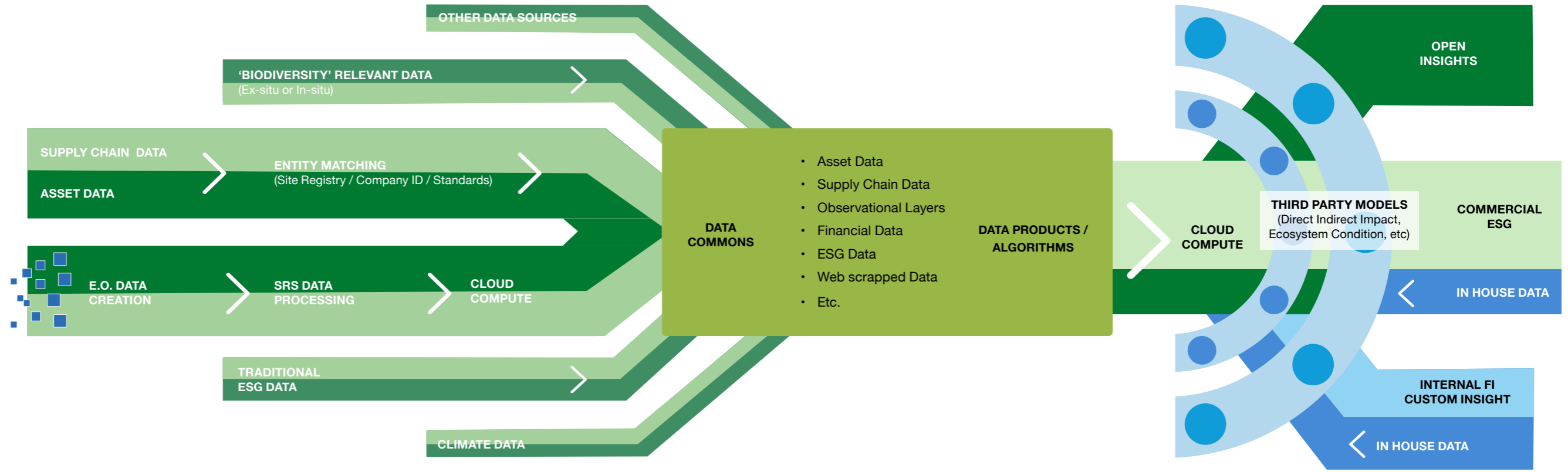
The OS-Climate Data Commons platform shows a possible path for solving data gaps in making biodiversity data more easily accessible, and being an open-source initiative, it can easily be adopted and extended to support the needs described in this document.

WHAT WOULD A DATA COMMONS FOR ‘BIODIVERSITY’ LOOK LIKE?

In the diagram (Figure 42), we show how different types of data – at an absolute minimum, asset and observational data (SRS-derived) – can be brought together to support a connected infrastructure of shared and third-party models to generate insight for commercial providers, to FIs, and openly.

Of course, additional complexity could be added, such as more data, supply chain data, improved entity matching components, water data, climate data, other ESG data sources, cloud compute, integration behind commercial actors’ firewalls to enable inhouse assessment with propriety data, etc. One important factor to consider is that a data commons can, as in the case of OS-C, support the flow of both open and commercial data into its systems, allowing users access to certain data only if they have paid for access.

Figure 42 – Diagram showing the major components a data commons for biodiversity and ecosystem insight would need to contain, pulling in both open (dark green) and commercial (light green) data.

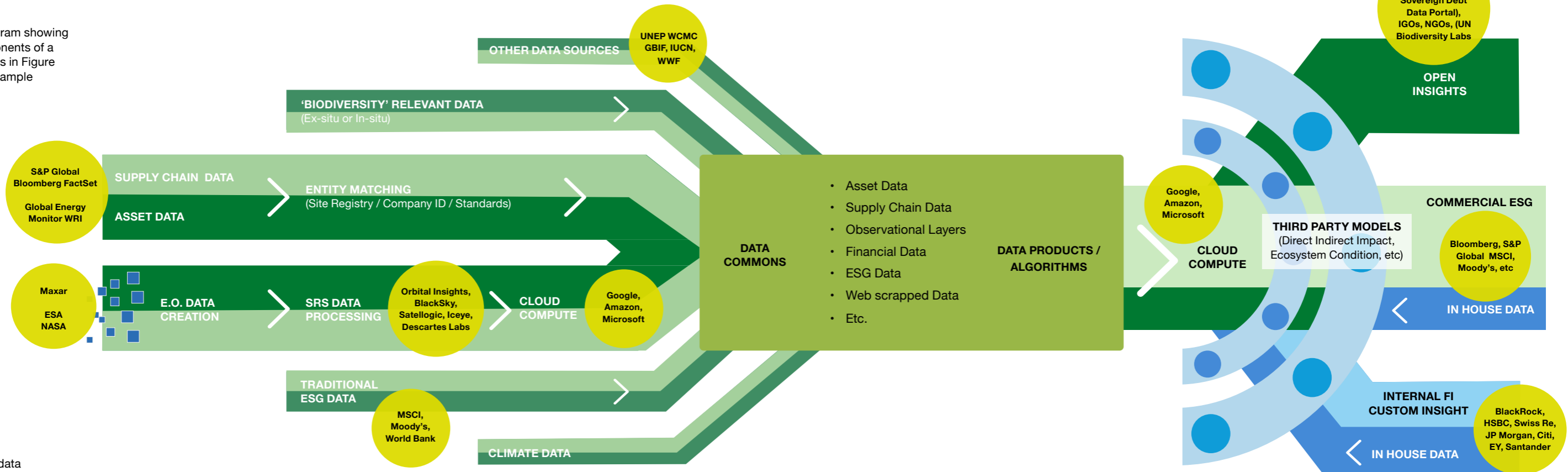


WHO WOULD BE INVOLVED?

Another way of looking at the data commons concept is to consider the types of actors likely to be involved and at which steps in the data ecosystem they would participate.

In Figure 43, we list some well-known companies as examples, making no actual inference as to which actors would or wouldn't be involved in such a data commons (Figure 43).

Figure 43 – Diagram showing the major components of a data commons as in Figure 42, along with example organisations.



BOX 6 – HOW WOULD THIS FIT WITH MAJOR TECH?

Author: Tanya Birch, Sr. Program Manager, Google Earth Engine / Earth Outreach

As the world moves towards spatially explicit insights and accountability of ESG investing, there's no shortage of available data from remote sensing and earth observation systems, and there are growing amounts of in-situ data streams to complement satellite data. With advances in machine learning and deep learning, earth observation systems and satellite data, cloud computing and emerging biodiversity monitoring systems, we have the ability to monitor the planet like never before.

While more nascent than satellite data, frequently updating data streams to measure biodiversity (acoustics, camera traps, eDNA) are rapidly advancing. As a result of platforms like Wildlife Insights, biologists no longer need to spend hours looking at images devoid of any species when producing species richness datasets, for example. Similarly, platforms like eBird and Merlin have made transformative advancements in bird identification, at least in areas of sufficient data like North America.

Still, people are drowning in data and thirsty for insights. Companies who tout their own climate and nature pledges without providing transparent empirical evidence to substantiate those claims are accused of greenwashing. As a solution, companies like Climate Engine, built on Google Earth Engine, exist to help de-risk financial portfolios from near-term and long-term severe weather events, providing data via APIs (Application Programming Interfaces) into other operational systems.

Nevertheless, biodiversity data is lacking, and there are many different disparate data sources that exist. The smooth coming together of satellite and in-situ data inputs and models will be the most helpful when presented in a manner that allows someone without a PhD in econometrics or remote sensing to derive insights from the data. The concept of a data commons, akin to the Open-Source Climate initiative, could support disparate biodiversity data streams aligning and providing insights to the countries and companies who are their ultimate end-users.

A data clean room, where companies upload private, sensitive data to a cloud instance that then gets aggregated and stripped of any private, personally identifiable or sensitive data, can be key to providing aggregates to a data commons. Companies straddle a double-edged sword in that they have to protect their proprietary data (e.g. their supply chain or investment portfolios) while at the same time releasing enough data, benchmarked against agreed-upon datasets and baselines, to meet standards around nature-risk or climate-risk and authentically understand the risk their investments present.

Earth observation data combined with biodiversity data streams could inform people making decisions affecting land use to substantiate 'nature positive' claims by companies and 30x30 claims by countries. A data clean room can also address security and privacy concerns around sensitive data (e.g. commercially proprietary data or sensitive endangered species data) with access control permissions intentionally agreed upon in a democratic manner. In a data commons, data and models can be made openly available, according to FAIR principles, especially when aggregated to remove sensitive data.

There are plenty of pledges from CEOs and governments to address individual and collective climate and nature risk. When a data commons exists, regulatory oversight, disclosures, penalties when satellite data and biodiversity data apply when a company or country is non-compliant. With governments, companies and NGOs/IGOs having access to a data clean room, sharing aggregated data that has been stripped of data sensitivities and personally identifiable information, combined with restrictions on data access and data use, the scientific community can support companies' ESG goals and help them not only de-risk their own portfolios but support the regulatory environment in shifting towards better practices across the industry at large.

HOW MIGHT A DATA COMMONS HELP OVERCOME CHALLENGES?

In this section we consider the advantages of working together via a data commons approach in resolving the following issues:

- **Challenge 1 – Asset Data**
- **Challenge 2 – Supply Chain Data**
- **Challenge 3 – Observational Data**

CHALLENGE 1 ASSET DATA: DEFINING THE LOCATION OF EVERY ASSET ON EARTH

Moving forward, we need viable approaches to generate and maintain asset datasets at scale. We need practical means to define, and critically maintain, all sectors' asset datasets, including those with millions of assets. Broadly speaking we see three current approaches to generating asset datasets (See Page 44): 1) proprietary, 2) open (manually created or via SRS or some ML method) or 3) open – community driven.

Which approach has potential?

Open asset datasets, such as WRI 'Global Power Plants' or 'Palm Oil Concessions', suffer from three major issues from a geospatial ESG perspective. First, they tend to be produced as a 'one-off' initiative with no resources for long-term maintenance; as they age without update, uncertainty around correct assignment of ownership mounts. Second, to date they have only proven capable of tracking a low number of assets, frequently applied to industries with low asset counts (≤5,000 assets), with no real demonstrated scalability. Those few examples over 50,000 assets either have gross errors, a lack of ownership information or, more often, face a multitude of issues. Third, they also tend not to capture key attributes consistently and contain greater error and data biases, such as recording only the assets of larger companies.

This is to be expected, as typically open asset datasets are built and launched to answer a specific research need and, due to the realities of funding restrictions, are unlikely to have been developed with the intention of long-term maintenance or geospatial ESG application.

To surmount these development and long-term maintenance challenges, one open data approach which shows greater potential is the open community-driven model. For example, Global Energy Monitor has built live asset datasets, maintained by an active online community. Even so, as shown in Figure 18, these track 1,000–10,000 assets, which is significantly lower than their commercial counterparts.

An alternative solution to the scaling issue for open datasets might be around coordination, where different open data actors could each work on one specific sector and together work towards wider tracking of assets. However, over long timeframes (5 years+), either within an open data or community-driven effort, how certain can we be that these datasets will be robust, that ownership is correct – for tens of millions of assets? The reality is that any open approach, with current technology, is unlikely to succeed at scale, and even if it does it is unlikely to be sustainable with the weight of maintenance always present month on month.

As-documented commercial offerings (See Page 44) provide far higher quality and viable data products for geospatial ESG application – and can be used for the sectors they already cover. The issue with the commercial approach is, will they invest to define other sectors where there is no historic or proven commercial business model to do so?

Instead, the most viable approach appears to be to place the burden of maintaining asset datasets back onto the financial sector and asset-owning companies themselves. Some corporates have called for an '**open asset registry**' within the data commons, which enables the systematic collection of asset data (with or without ownership, with differing discoverability and access), uploaded by the corporates themselves, via financial sector incentives. The development of such an initiative should be mandated and tasked to initiate and operate the registry, based on open technology. Such an effort could be launched rapidly and could be a first step forward in a longer-term push for regulation and disclosure efforts, requiring companies to report the location of their direct holdings into such an ecosystem. Within this data ecosystem, existing open and commercial asset datasets could still be connected in, as required.

Of course, regulation and disclosure developments should also be supported, but it seems unlikely, due to the timescales of regulation, that such data will be available within the short term.

CHALLENGE 2

SUPPLY CHAIN DATA: DEFINING THE DYNAMIC SUPPLY CHAINS OF EVERY COMPANY ON EARTH

Without supply chain data it will remain very difficult to estimate the true impact of actors within high-tier industries. This is because the higher up the supply chain, the less likely it is that the business requires direct interaction with the natural world (Figure 14). However, this does not mean they are less likely to be drawing from, or enabling via supply chains, impacts to the natural world.

For example, a major car manufacturer is unlikely to clear pristine rainforest for its headquarters or regional offices, but it may be sourcing its raw materials from mines which are. Knowledge of each asset's performance, and supplier's asset performance, would allow the car manufacturer itself to act or even change supplier if necessary. It would also provide the FIs with improved oversight of the 'biodiversity' implications associated with the car manufacturer and the ability to flag the problematic assets with the company.

The most significant impacts are often present at the ends of supply chains, often held by private, junior, effectively unaccountable actors. Transparency as to which accountable actors (listed companies) are doing business with these asset holders within their supply chains is a requisite to reducing incentives and markets for these operations.

Unfortunately, supply chain data is very difficult to gain access to; even the commercial business intelligence providers have struggled to make headway in this space, often having to rely on effectively reverse engineered and estimated connections. Indeed, in many cases companies themselves will not know the full extent of their supply chains; for example, a supermarket might know that it buys its oranges from wholesaler X, but then no further down the supply chain.

Due to the data gaps, and significant data sensitivities around supply chain data, where for competitiveness reasons companies may not wish others to know their suppliers. It is difficult to envision any possible solution within the next 12–24 months which moves supply chain data into a more public sphere. What might, however, be possible is the creation of 'supply chain data sharing standards' attached within the data commons infrastructure, to allow a company to securely share their supply chain data with a specific FI for analysis behind the FI's firewall. This act could be incentivized by the financial sector, slowly normalizing the approach as part of the due diligence process.

CHALLENGE 3

BASELINES / OBSERVATIONAL DATA / METRICS / IMPACT ADJUSTMENT

The development of the metrics, baselines and key indicators necessary to provide insight from geospatially driven approaches is still in its infancy.

As we move forward, there is the danger that commercial operators keen to capitalize on the emerging market will, faced with data limitations, release sub-par data products. This creates two issues: 1) it undermines the emerging field and 2) it will help normalize low-quality insight within the field.

To resolve this, various actors will need to move quickly to establish high data standards by creating widely accepted and peer-reviewed data products themselves (e.g. baselines, route impact layers, etc). Standards and research will need to be conducted to test and publicly review those products released, to highlight limitations and strengths within the emerging field.

FINAL THOUGHTS

Our ability to move forward with biodiversity and ecosystem insight, and indeed wider **climate** and social and governance insights, will rest heavily on the available asset, supply chain and financial data. Without this 'baseline data', multiple fields of research will stagnate. The flow of this data, then, is not just relevant for the 'nature-related' insights but potentially across all ESG topics.

It is important to reflect on one major point. While the space is complex – it is viable. No new technology is required. However, who's going to do it? Who's going to establish open standards and build the necessary public good data infrastructure? Commercial ESG actors will be motivated to ensure that they have the most robust data offerings in this space, developing, as far as possible, their own geospatial ESG insights and methods. However, their progress will be limited unless the extensive public good parts of the equation (e.g. standards, data infrastructure) are also resolved.

In this publication, we have called for a new, independent, unaffiliated 'centre' to deliver the components outlined here, to ensure that the flow and power of the SRS sector can be brought to bear to factor in nature externalities within the financial sector. This follows developments such as the Met Office Hadley Centre, established by the UK government in 1990 to aid climate change research.

The development of a geospatial ESG data commons, and a 'centre' to oversee developments, has several major advantages:

- Its moves us away from the current situation, which is not delivering insight. It is 'a flashlight in the dark', which only provides insight on the single assets or company the light is focused on, and where currently FIs must pay and login to multiple (5+) unconnected platforms to run assessments themselves. It moves us to a model where all the information is widely available, already processed and analysed, and integrated into the business intelligence world.
- It will allow the NGO/IGO a viable payment structure for their data products, with wide reach connecting across platforms and with low management overhead, as the data infrastructure is provided for them.
- It provides a centralized, authoritative place for methods, models and approaches to be tested, iterated and assessed by the community and domain experts.
- It will allow the FIs and Business Intelligence providers access to SRS data products, in one place, without the need for dialogue with a wide variety companies.
- It will streamline and, in many cases, provide a new business opportunity for the SRS community.
- It aligns and supports data needs in other areas, such as climate change, which can apply the same asset and supply chain and even 'environmental' variables to support climate insight, and potentially social and governance insight.

The question we face now is, 'Can we move quickly enough, within the next 12 months, to radically improve 'E' within modern ESG?'

RECOMMENDED ACTIONS

We suggest the following key actions, to radically improve biodiversity insight at the scale required.

- **JOIN THE CONVERSATION** – To push forward the concepts outlined in this document, WWF will shortly launch a 'Geospatial ESG Consortium'. We welcome financial institutions, conservation actors, tech, earth observation, remote sensing, ESG providers, etc. interested in the emerging field to join us.

- **CREATE A 'BIODIVERSITY DATA COMMONS'** – We need to move away from siloed, standalone platforms to a 'platform of platforms' federated approach which enables improved data access and interoperability of asset and supply chain data, and observational data – integrating into the financial sector's data ecosystem.

Action – A 'data commons' needs to be established to enable actors to share critical asset and observational data, models or approaches – openly, securely or behind an FI's firewall – with robust standards. This needs to radically improve access to critical asset and supply chain data to enable assessment and, critically, the building, sharing and iteration of models and methods.

- **CHANGE CORPORATE DATA DISCLOSURE / ACCESS** – Every asset on Earth needs to be geolocated, and accessible in either open or proprietary datasets (within the data commons). Ownership must be accurately maintained, and ideally asset datasets should be sector specific, capturing wider attributes and defining the property boundaries.

Action – An 'asset registry' is needed within the data commons, uniting via a federated approach, ongoing open data disclosure and regulation initiatives. While placing the primary burden of generating and maintaining asset datasets and company trees onto the corporates.

Action – Develop means to enable the sharing of supply chain data between a corporate and FI securely within the data commons.

- **DEVELOP AND REFINE OBSERVATIONAL DATA** – Clarity needs to be created around biodiversity and ecosystem observational data, defining robust metrics. Metrics need to be tested and openly reviewed as to their ability to detect the variable under measurement.

Action – The 'biodiversity' community should:

- Align to existing efforts such as GEO BON and GBIF; provide support and iterative guidance as to which observational datasets, and the metrics derived therefrom, are scientifically robust and how they might be improved.

Action – The Satellite Remote Sensing (SRS) communities should:

- Align to existing efforts, and collectively identify spatial or temporal gaps and any possible means of improvement of the observational data portfolio, either via more regular higher-resolution data gathering or alternative solutions.

- Explore with the wider community novel approaches, such as data triangulation, or the testing of specific novel metrics.

- **DEVELOP AND REFINE METHODS AND MODELS** – As an emerging field, the core methods of geospatial ESG for biodiversity and ecosystem insight remain fluid. Critically, areas such as the framework, area delineations, global baselines and models determining topics such as, indirect impacts or landscape condition, need to be collectively worked through.

Action – Researchers (perhaps via structured working groups) need to provide clarity on the optimal methods and approaches. Results should be peer reviewed and published when possible.

- **CREATE STANDARDS** – Across all this work – ranging from basic arrangements for asset datasets to data security protocols – soft, technical standards need to be developed.

Action – Open-source standards need to be rapidly deployed to aid developments – a large resource of existing technical standards exists which could be adopted.

- **ALIGN WITH CLIMATE** – Many of the data needs of the 'biodiversity' space directly align with the needs of the climate space and wider ESG needs. Almost all ESG efforts, for example, would benefit from improved access to financial data, asset data and supply chain data. While eventually, since climate and nature are interlinked issues, the two will need to be considered together, as and when the data science allows.

Action – Engage with 'climate data actors' early on, when developing data commons, frameworks, metrics, standards, etc., to identify opportunities for alignment.

- **EDIT TO: CREATE A 'CENTRE' TASKED WITH DELIVERING THE INCLUSION OF CLIMATE AND NATURE GEOSPATIAL INSIGHTS INTO THE FINANCIAL SYSTEM** – Ultimately if no-one is made responsible for the above, it is likely that progress will stagnate, with commercial actors unable to resolve the public good aspects of the equation. To ensure the work is delivered, an independent international research centre needs to be established – connected with existing efforts but tasked and resourced to ensure the delivery of SRS data, methods, models and public data utilities to aid localized, regional biodiversity and ecosystem insight and interlinked social and climate issues.

Action – The government/s which take the initiative on the establishment of such a centre or federated model will place themselves at the heart of the next revolution: the inclusion, via the full weight of the SRS sector's power, of environmental and climate externalities into the financial system.



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ENDNOTES

1 Where possible we have made attempts to align the terminology used within this document with that adopted by the Taskforce on Nature-Related Financial Disclosures (TNFD).

2 Science-Based Targets Network (SBTN), Taskforce on Nature-related Financial Disclosures (TNFD) and the European Sustainability Reporting Standard (ESRS).

3 WEF, 2022

4 WWF, World Bank and Global Canopy, 2022

5 Biodiversity can be defined loosely as the variability among living organisms. The term is increasingly used within the financial community as a byword for anything related to ‘nature’ or the ‘natural world’. Within the ESG space, there are a wide range of data products that present, or could potentially provide, proxy insights relevant to biodiversity and as such are often communicated around or within the ‘biodiversity’ label. For example, a wide range of indirect geospatial proxies, such as ‘freshwater extraction’ or ‘legal area delineations’, are used, which without being a direct measure of biodiversity, may still arguably provide useful insight.

However, for reference, a more complete definition of biodiversity is from the United Nations Convention on Biodiversity (CBD), ‘The variability among living organisms from all sources, including, inter alia, terrestrial, marine and other aquatic ecosystems and the ecological complexes of which they are part; this includes diversity within species, between species and of ecosystems’ (CBD, 1992).

6 Where X could be a specific development for project level finance, a corporation, a portfolio, a sovereign state or any other variable of interest.

7 Throughout this document we’ve tried to discuss matters simply to aid understanding for a non-biocentric audience; however, it is important to note that many of the points made here are generalized and are not meant as robust conservation science statements.

8 An ecosystem is defined as ‘a dynamic complex of plant, animal and microorganism communities and the non-living environment, interacting as a functional unit’ (CBD, 1992)

9 Cardinale et al., 2012

10 Where X could be a specific development for project level finance, a corporation, a portfolio, a sovereign state, or any other variable of interest.

11 Ceballos et al., 2015

12 Complete recovery from prior major extinction events took tens of millions of years. The Ordovician required 25 million years, the Devonian 30 million years, the Permian and Triassic so close together took 100 million years, Cretaceous 20 million years. There have been authors, who have suggested that the mixing of species (by humanity moving invasive species around the world), will fill the extinction gaps caused by humanity, and that extinction events were followed by a surge of new species. Combined, this will result in a wealth of biodiversity. This may one day be the case; however, we know it will take millions of years of the cogs of the ecosystems to work themselves back into viable arrangements.

13 We use the terms direct and indirect with a slightly differing terminology, to better align to the observational data capabilities (See Glossary).

14 Soto et al., 2022

15 Endemism refers to species restricted to a single specific location, area or region.

16 Stewart and Konar, 2012

17 Rogers-Bennett and Catton, 2019

18 Rasher et al., 2020

19 NASA, 2013

20 NASA, 2020

21 ESA, 2022

22 ESA, 2022b

23 Duke et al., 2017

24 Swiss Re Institute, 2020

25 We acknowledge that improvements in conservation science driven by new technology and methodologies, such as landscape audio and environmental DNA, offer potentially new means for large scale in-situ field data collection which may be relevant for geospatial ESG applications (See World Bank and WWF (2020)) – however, currently these approaches are not yet able to provide insight at scale, nor does it appear likely that will offer insight within the immediate future (next 5 years).

26 ForestGEO, 2022

27 Edge effects can be defined as ecological alterations linked with development of sudden, artificial edges of forest fragments.

28 Environmental Justice Atlas, 2016

29 *Location: 16°51’41.09”N 89°00’47.56”W*

30 Probe International, 2009

31 Probe International, 2009

32 Canadian International Development Agency, 2016

33 Plumptre et al., 2022

34 Kennedy et al., 2019

35 Grantham et al., 2020

36 Kennedy et al., 2019

37 Sanderson et al., 2002

38 McGarigal et al., 2018

39 Tierney et al., 2009

40 Anderson, Clark and Sheldon, 2014

41 Anderson, Clark and Sheldon, 2014

42 Gunderson, 2000

43 Brown and Williams, 2016

44 Faber-Langendoen et al., 2012

45 Andraesen et al., 2001

46 McGarigal et al., 2018

47 GEO BON, 2019

48 Haase et al., 2018

49 *Ibid.*

50 Robeco, 2022

51 Ministère de L’économie des Finances et de la Souveraineté Industrielle et Numérique, 2021

52 European Commission, 2022

53 EFRAG PTF-ESRS, 2022

54 CDP 2022 Questions on Biodiversity:

(C15.1) Is there board-level oversight and/or executive management-level responsibility for biodiversity-related matters within your organization?

(C15.2) Has your organization made a public commitment and/or endorsed any initiatives related to biodiversity?

(C15.3) Does your organization assess the impact of its value chain on biodiversity?

(C15.4) What actions has your organization taken in the reporting year to progress your biodiversity-related commitments?

(C15.5) Does your organization use biodiversity indicators to monitor performance across its activities?

(C15.6) Have you published information about your organization’s response to biodiversity-related issues for this reporting year in places other than in your CDP response? If so, please attach the publication(s).

55 World Resource Institute, 2022

56 Ecometrica, 2022

57 Maphubs, 2022

58 Integrated Biodiversity Assessment Tool (IBAT), 2022

59 Asset Resolution, 2022

60 Verisk Maplecroft, 2022

61 Reprisk, 2022

62 See Finance for Biodiversity (2022) for a detailed overview of these approaches.

63 Climate Arc, 2022

64 CDP, 2022

65 TNFD, 2022b

66 TNFD, 2022c

67 EFRAG PTF-ESRS, 2022

68 Mollod and Klug, 2022

69 Greer, Sim and Koplinski, 2022

70 Mollod and Klug, 2022

71 Mollod and Klug, 2022

72 Pütz, et al., 2014

73 Pütz, et al., 2014

74 We refer to these firms – Bayerische Motoren Werke AG and Mercedes-Benz Group AG – purely as examples of famous major companies, with no implication or suggestion of any negative or positive ecosystem and biodiversity impacts.

75 Robeco, 2022

76 Agrillo et al., 2022

77 See Page 77.

78 Aggregation of results will inevitably meet complexities as we attempt to unite differing asset classes: different geospatial metrics or traditional ESG data points are sector specific and may not be present or comparable with other sector specific metrics – for example, a metric for cotton farming pesticide use (within a major clothing manufacturer’s supply chain) may not fit with marine oil spill detection (within a major O&G company) within a portfolio scoring. See Page 43 on quantification of metrics.

79 WWF, World Bank and Global Canopy, 2022

80 Global Energy Observatory et al., 2019

81 This dataset combines different oil and gas assets all as ‘units’, defining different instances of level, field, block, project, concession, complex, basin, pool, area, unit, region, and sub-basin within the same dataset.

82 Kruitwagen et al., 2021

83 This dataset reports 68,661 assets. However there is significant error rate, with many ‘unique’ records reporting the same asset.

84 Enverus additionally provide detailed asset coverage across a range of O&G asset types (e.g. concessions, surveying pipelines, rigs, etc.)

85 Maus et al., 2020

86 The geolocation of every asset might sound ambitious, but from a technical standpoint it is viable –complex, asset-rich sectors have already been mapped (e.g. oil and gas), and already, far more ‘asset level’ data are collected in Google Maps than are required for geospatial ESG requirements.

87 DAMSAT, 2022

88 TNFD, 2022d

89 EFRAG PTF-ESRS, 2022

90 See WWF, World Bank and Global Canopy (2022) for a detailed explanation.

91 Chang et al., 2021

92 WWF, World Bank and Global Canopy, 2022

93 Data dependant – assuming access to suitable data.

94 Hydrosheds, 2020

95 We propose the use of water basins, but of course, other any regional definitions can be applied for wider landscape (L) context, such as state or municipality; multiple regional definitions can be used at once.

96 Geospatially defined global ‘biodiversity’ and/or ‘ecosystems’ baselines arguably already exist in various forms (See Page 69). However, there is a need to develop robust, widely backed ‘historic’ baselines and establish standards for geospatial ESG application.

97 Sandom et al., 2014

98 DEFRA, 2013

99 Gaston, 2000

100 Pontarp et al., 2019

101 Hillebrand, 2004

102 Judas, 1988

103 Gaston and Blackburn, 2007

104 Griffiths, 1997

105 Patterson, et al., 1998

106 O’Brien, 1993

107 Jetz, McPherson and Guralnick, 2012

108 Marsh et al., 2022

109 Olson et al., 2001

110 Dinerstein et al., 2017

111 GEO BON, 2022

112 Half-Earth Project, 2022

113 NatureServe, 2022

114 There is across nature-related insight efforts an increasing complexity within the terminology used. Here for a non-technical audience, we attempt to keep the terminology as straightforward as possible. We define ‘impact’ as an attribute event, either natural or human-made, that adversely alters the status of ecosystem condition (See Glossary).

115 Within the natural capital terminology, an impact is different to an impact driver. Impacts are ‘changes in the quantity or quality of natural capital that occurs as a consequence of an impact driver’. Impact drivers are defined as: ‘a measurable quantity of a natural resource that is used as an input to production or a measurable non-product output of business activity.’ (Natural Capital Coalition, 2016).

116 As climate change impacts make such events more likely, these impacts, as a minimum, averaged landscape risk weightings could be applied to adjust results.

117 We apply a different definition of ‘direct’ and ‘indirect’ impacts, which traditionally are defined by causation: impacts known to be directly caused by operator X. Here we drop the need to define causation, since often it is impossible to know with certainty which impacts are directly caused of a company’s operations (See Glossary).

118 Gerson et al., 2022

119 *Ibid.*

120 Ackerman et al., 2016

121 WWF, 2018

122 Steckling et al., 2017

123 Worse still, it almost entirely avoidable; the mining technologies exist to reduce the amount of mercury required, or capture mercury used during the gold purification process before its release. It is likely that illegal miners are not aware of the risks, or unable to afford the equipment.

124 Kea Conservation Trust, 2022

125 Due to the complications of route identification, where thousands of potential routes may be present between two assets, it would appear simplest now to focus on estimated transportation impacts via the single shortest possible route, although of course more accurate, intelligent route selection can be applied.

126 Natural England, DEFRA and Pow, 2021

127 GLOBIO, 2022

128 Hettler, 2022

129 Audubon, 2022

130 We suggest the use of water basins over ecoregions, as they align to natural processes (loosely aligned to ecosystems and biodiversity and are non-subjective), and due to the technical difficulty in defining the borders of current ecosystems.

131 WWF, 2022

132 Tickner et al., 2020

133 Dickens et al., 2021

134 NASA SWOT, 2022

135 Grill et al., 2019

136 Opperman et al, 2021

137 Kuehne et al., (*in prep*)

138 Deltares. (2021).

139 Feio et al., 2022

140 Forzieri et al., 2022

141 Climate Arc, 2022

142 There is arguably a comfort with the status quo, where some FIs may be more at ease with higher levels of uncertainty around biodiversity and ecosystem impact. Moreover, some data providers may be keen to continue unchanged the provision of their products. Regardless, it seems that a growing body of FIs agree that ‘biodiversity’ insight can be improved and that it is a priority to do so considering the wider implications.

143 Some FIs have worked to scale their internal geospatial ESG capacity, which should be welcomed; however, while it will give them a significant advance in understanding such data, it is impossible for any single inhouse team to deliver a complete geospatial ESG ecosystem.



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To stop the degradation of the planet's natural environment and to build a future in which humans live in harmony with nature.

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