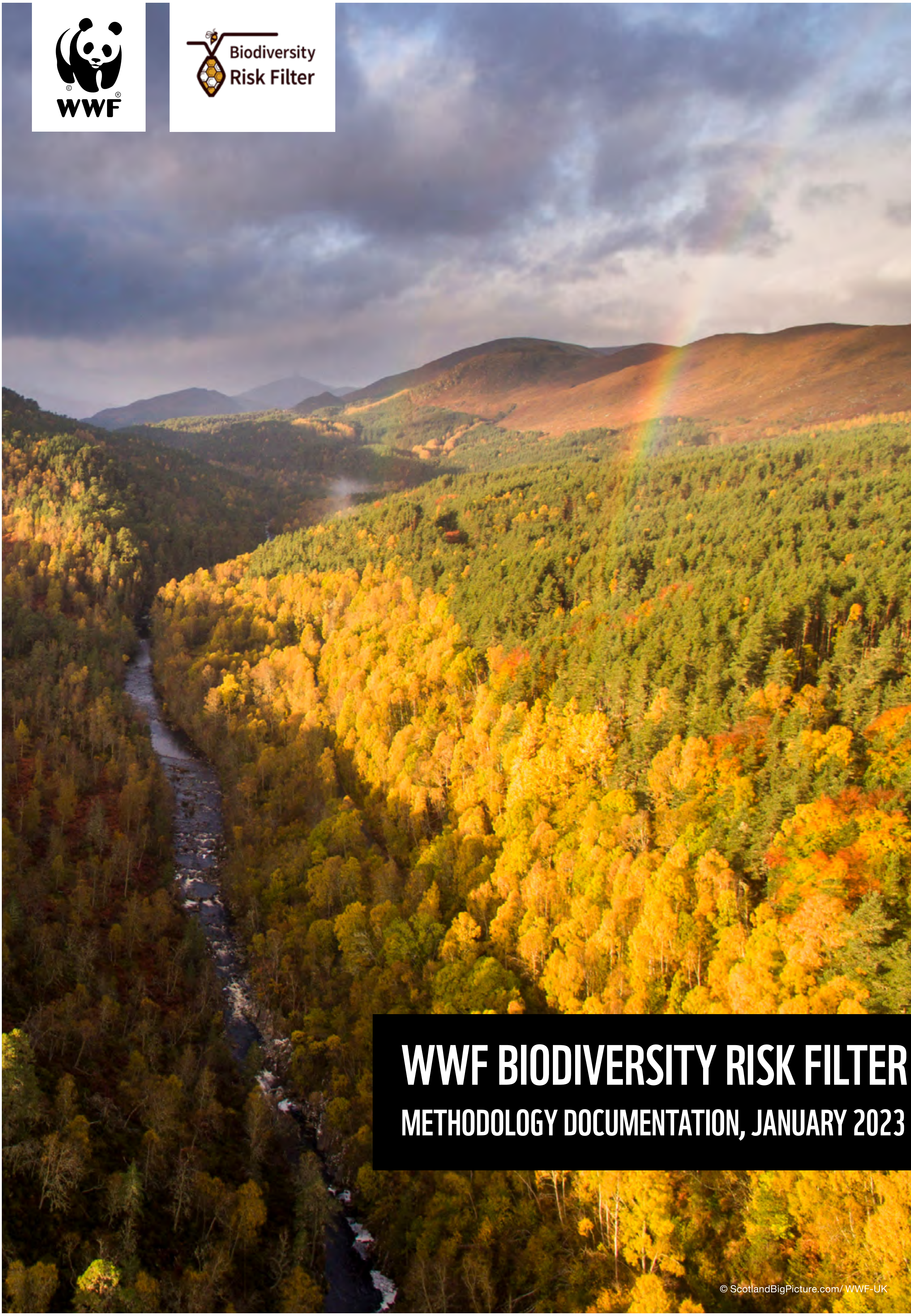

WWF BIODIVERSITY RISK FILTER

METHODOLOGY DOCUMENTATION, JANUARY 2023

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The WWF Biodiversity Risk Filter tool methodology

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WWF Biodiversity Risk Filter additional methodological guidance A-C

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About WWF

WWF is one of the world's largest and most experienced independent conservation organisations, with over 5 million supporters and a global network active in more than 100 countries. WWF's mission is to stop the degradation of the planet's natural environment and to build a future in which humans 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.

About Climate & Company

Climate & Company is one of Europe's leading sustainable finance think-tanks. We are a group of mission-driven experts on climate and biodiversity finance and policy from key EU institutions, the academic world and the banking and investment sectors. As a team, we make sustainable development a reality by acting as bridge-builders between the private and public sectors, supporting evidence-based policy-making, and creating international partnerships and fora for international knowledge exchange.

CONTENTS

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TABLE OF FIGURES

TABLE OF TABLES

LIST OF ABBREVIATIONS

BIA-GBS	Biodiversity Impact Assessment powered by the Global Biodiversity Score
BICS	Bloomberg Industry Classification Standard
BNEF	Bloomberg New Energy Finance
BRF	Biodiversity Risk Filter
C4F	Carbon 4 Finance
CGP	China's Global Power
ENCORE	Exploring Natural Capital Opportunities, Risk and Exposure
FAO	Food and Agriculture Organization
GHG	Greenhouse gas (emissions)
GLOBIO	Global Biodiversity Model for Policy Support
IBAT	Integrated Biodiversity Assessment Tool
ISIC	International Standard Industrial Classification
LEAP approach	Locate, Evaluate, Assess, Prepare Approach
MRIO models	Multi Region Input-output models
MSCI ACWI	Morgan Stanley Capital International All Country World Index
NACE	Nomenclature of Economic Activities
NAICS	North American Industry Classification System
NUTS 3	Nomenclature of Territorial Units for Statistics 3
RRTS	Relative Realised Timber Services
SBTN	Science Based Targets Network
SFI	Spatial Finance Initiative
SME	Small and medium-sized enterprises
TNFD	Taskforce on Nature-related Financial Disclosures
WBCSD	World Business Council for Sustainable Development
WRF	Water Risk Filter

KEY TERMS

Term	Definition
Abiotic	A non-living part of an ecosystem that shapes its environment. In a terrestrial ecosystem, examples include temperature, light and water. In a marine ecosystem, abiotic factors include salinity and ocean currents. Abiotic and biotic factors work together to create the overall ecosystem (National Geographic, 2022).
Biodiversity	The variability among living organisms from all sources, including, among other things, 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). In other words, biodiversity is the part of nature that is alive, and includes every living thing on earth (see also the definition of nature, below).
Biodiversity footprint	The impact of a commodity or company on global biodiversity, measured in terms of biodiversity change as a result of production and consumption of particular goods and services.
Biodiversity loss	The reduction or disappearance of any aspect of biological diversity in a particular area through death (including extinction), destruction or manual removal. It can refer to many scales, from local population declines to global extinctions, resulting in reduced total diversity at the same scale (IPBES, 2022a).
Biodiversity-related opportunities	Activities that create positive outcomes for organisations and biodiversity by avoiding or reducing impacts on biodiversity or by contributing to its restoration. Biodiversity-related opportunities can go beyond common sustainable business archetypes to include actions that companies can take to influence the threats and pressures driving biodiversity loss and degradation globally, both within their value chains and in the places where they operate (WWF, 2022a).
Biodiversity-related risks	Potential threats posed to an organisation linked to its and other organisations' impacts on biodiversity and dependencies on ecosystems. These can derive from physical, transition and systemic risks.
Biotic	A living organism that shapes its environment. In a freshwater ecosystem, examples include aquatic plants, fish, amphibians and algae. In a terrestrial ecosystem, examples include terrestrial plants, fungi, insects, amphibians and mammals. Biotic and abiotic factors work together to create the overall ecosystem (National Geographic, 2022).
Business importance of site	The economic importance of a specific company location (i.e., site) in relation to the overall company performance. The business importance of a site can be determined on the basis of financial variables, such as revenues or sales, or on the basis of expert opinion.
Dependencies on biodiversity	Aspects of ecosystem services that an organisation or other actor relies on to function. An organisation might be dependent upon an ecosystem's regulation of water flow and quality, the resilience it provides against hazards like fires and floods, the pollination of crops it enables by providing a suitable habitat for pollinators, or its provision of timber or fibres.[1]
Direct drivers of biodiversity and ecosystem change	Drivers, both natural and human-induced, that unequivocally affect biodiversity, ecosystems and nature directly (also referred to as pressures). These drivers in turn affect the provision of ecosystem services with consequences for people, the economy and society. The main direct drivers of biodiversity and ecosystems loss are land, water and sea change, climate change, pollution, natural resource use and exploitation and invasive species (IPBES, 2022b).
Ecosystem	A dynamic complex of plant, animal and microorganism communities and their non-living environment, interacting as a functional unit (CBD, 1992; IPBES, 2019a).
Ecosystem condition	The quality of an ecosystem 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 (TNFD, 2022a).
Ecosystem function	The flow of energy and materials through the biotic and abiotic components of an ecosystem. This includes processes such as biomass production, trophic transfer through plants and animals, nutrient cycling, water dynamics and heat transfer (IPBES, 2019a).

1 Based on SBTN working definition, unpublished.

Term	Definition
Ecosystem (Biodiversity) integrity	The ability of an ecosystem to support and maintain ecological processes and a diverse community of organisms. The ecological integrity of ecosystems, as it is also known, is measured as the degree to which a diverse community of native organisms is maintained, and is used as a proxy for ecological resilience, or the capacity of an ecosystem to adapt in the face of stressors while maintaining its functions and services of interest (IPBES, 2022a).
Ecosystem services	The contributions of ecosystems to the benefits that are used in economic and other human activity (UN , 2021). TNFD (2022b) defines ecosystem services as falling into one or more of the following categories: • **Provisioning services** represent the contributions to benefits that are extracted or harvested from ecosystems (e.g., timber and fuel wood from a forest, fresh water from a river). • **Regulating and maintenance services** result from the ability of ecosystems to regulate biological processes and to influence climate, hydrological and biochemical cycles, and thereby maintain environmental conditions beneficial to individuals and society. Provisioning services are dependent on these regulating and maintenance services (e.g., the provision of crops depends upon relatively stable climate, hydrological and biochemical cycles). • **Cultural services** are the experiential and intangible services related to the perceived or actual qualities of ecosystems whose existence and functioning contributes to a range of cultural benefits (e.g., the recreational value of a forest or a coral reef for tourism).
Impacts on biodiversity	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 (TNFD, 2022a).
Materiality	A concept that defines why and how certain issues are important for a company or industry sector. A material issue can have a major impact on the financial, economic, reputational or legal aspects of a company, as well as on the system of internal and external stakeholders of that company. Although the concept applies in a wide variety of contexts (e.g., accounting, reporting, etc.), in this report materiality refers to biodiversity and water aspects affecting the financial performance of companies ("outside-in") and how they and their activities impact biodiversity and nature ("inside-out") (TNFD, 2022b; IPSF; Climate & Company, 2021).
Nature	The natural world, with an emphasis on the diversity of living organisms (including people) and their interactions among themselves and with their environment (TNFD, 2022a). In other words, nature is all life on Earth (i.e., biodiversity), together with the geology, water, climate and all other inanimate components that comprise our planet (see also the definition of biodiversity, above).
Natural capital	The stock of renewable and non-renewable natural resources (e.g., plants, animals, air, water, soils and minerals) that combine to yield a flow of benefits to people (Capitals Coalition, 2016).
Nature loss	The loss and/or decline of the state of nature. This includes, but is not limited to, the reduction of any aspect of biological diversity, e.g., diversity at the genetic, species and ecosystem levels in a particular area through death (including extinction), destruction or manual removal (TNFD, 2022a).
Nature-related opportunities	Activities that create positive outcomes for organisations and nature by avoiding or reducing impacts on nature or by contributing to its restoration. Nature-related opportunities can occur i) when organisations mitigate the risk of natural capital and ecosystem service loss and ii) through strategic transformation of business models, products, services or investments that actively works to halt or reverse the loss of nature, including by the implementation of nature-based solutions (or support for them through financing or insurance) (TNFD, 2022a).
Nature-related risks	Potential threats posed to an organisation linked to its and other organisations' impacts and dependencies on nature. These can derive from physical, transition and systemic risks (TNFD, 2022a).
Scape risk	The term scape is used to refer collectively to landscapes, seascapes and river basins (freshwater systems). Scape risk is informed by a company's geographic location, it's industry sector and the integrity of biodiversity and ecosystems at the geographic location.

INTRODUCTION:
THE WWF BIODIVERSITY RISK FILTER

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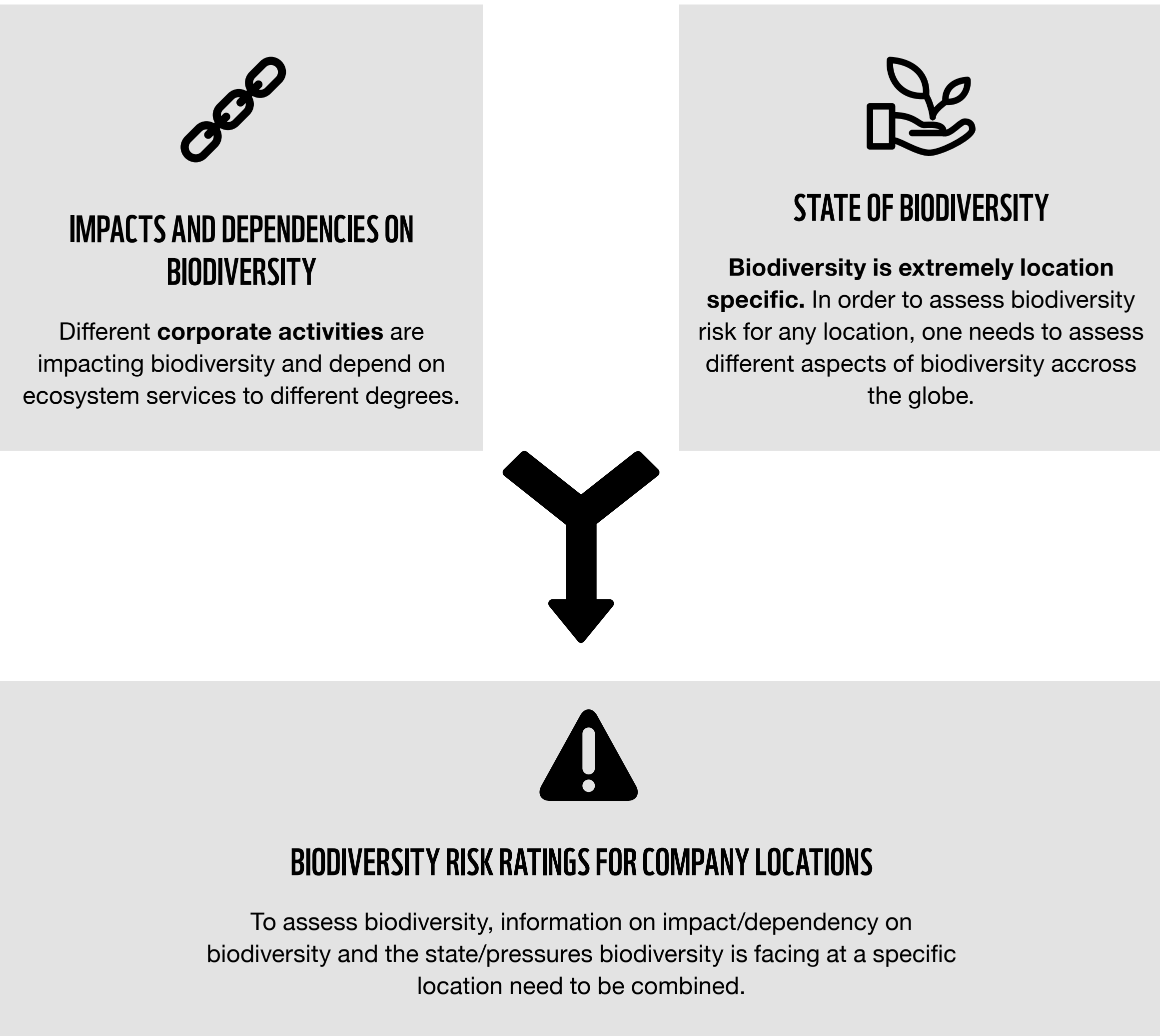
Biodiversity-related risks arise from companies' dependencies and impacts, in combination with importance and local and global state of biodiversity integrity. As the importance and state of biodiversity integrity can vary across the location of company sites, the assessment of biodiversity-related risks, response options and progress need to be location-specific as well (see Figure 1). Understanding and addressing biodiversity-related risks is vital for companies and financial institutions but is challenging as location-specific data is necessary (SBTN, 2020a; TNFD, 2022b). Without location-specific biodiversity (i.e., data on the importance and integrity of biodiversity) and company data (i.e., location of company sites, industry classification and business importance of the site), it is difficult for companies and financial institutions to fully understand their biodiversity-related risks and prioritise areas for action. Such an analysis requires a tool that can analyse the relevant and available spatially explicit biodiversity data and link it to the company locations.

Responding to this need, WWF has launched the Biodiversity Risk Filter (BRF), building on WWF's long-standing expertise and experience with the Water Risk Filter (WRF).

The following sections describe the objectives and deliverables, the scope of the WWF BRF and the structure of this methodology documentation.

Figure 1: Biodiversity-related risk assessment as a combination of the location of corporate activities and the importance and state of biodiversity integrity



1. OBJECTIVES

The WWF Biodiversity Risk Filter currently consists of:

1. **The WWF Biodiversity Risk Filter**
2. **The WWF Biodiversity Risk Filter Methodology Documentation**

The WWF Biodiversity Risk Filter

The WWF BRF is a free-of-charge, web-based, spatially explicit corporate- and portfolio-level screening and prioritisation tool for biodiversity-related risks. It allows companies to understand and assess the biodiversity-related risks of their operational locations and their suppliers and to prepare an appropriate response plan. By the same logic, financial institutions can assess biodiversity-related risks for all companies in a given portfolio.

The tool builds heavily on WWF's experience with the WRF, launched in 2012 (WWF Water Risk Filter, 2021). In essence, both tools are designed to be used by companies and financial institutions for company- and portfolio-level screening and prioritisation to identify risk hotspots across companies' operational and supply chain sites. By using spatially explicit data on biodiversity and freshwater at global scale, the tools provide location-specific and industry-specific assessments of biodiversity and water-related physical, regulatory[2] and reputational risks. The tools aim to help companies and financial institutions to better prioritise where and on what to focus contextual responses as well as inform their biodiversity- and water-related stewardship strategies and target setting.

Both tools are available through the *WWF Risk Filter Suite*. This integrated platform has a common user database. That means that users only need to enter the required location-specific company data once and can manage both tools in one central location. Once the data is added, the users can assess their biodiversity- and water-related risks.

The current version of the WWF BRF tool consists of three key modules: the Inform Module, which provides an overview of the industry-specific dependencies on ecosystem services and impacts on biodiversity; the Explore Module, which is a collection of spatially explicit maps of the importance and local integrity of biodiversity; and the Assess Module, which contains a tailored physical and reputational risk assessment for which users need to input location-specific company and/or supply chain data. A fourth module, the Respond Module, is currently under development. This will support users in identifying suitable actions to respond to the identified risks. In addition, it will include guidance on where to get more specific information on biodiversity values in a particular identified high-risk site via complementary tools such as the *Integrated Biodiversity Assessment Tool* (IBAT). Figure 2 summarises the key modules of the WWF BRF tool.

Figure 2: The four modules of the WWF BRF tool

INFORM MODULE	**Industry materiality:** Explore different industry sectors' dependencies on ecosystem services and impacts on biodiversity using an interactive table that lets you select the industries you are interested in.
EXPLORE MODULE	**Maps on the importance and integrity of biodiversity:** Explore maps of different biodiversity aspects at different geographical scales. The maps show high-risk regions to identify priority areas for action.
ASSESS MODULE	**Assessment of company and supply chain locations:** Upload your location-specific company and supply chain data for a tailored assessment of biodiversity-related physical and reputational risks of your operational sites, supply chain sites or your portfolio companies' sites respectively.
RESPOND MODULE	**Under development:** Draw up a suitable catalogue of response measures per site or across sites based on the individual risk assessment (i.e., the Assess Module).

2 Please note that the January 2023 version of the WWF BRF tool still needs to include the regulatory risk assessment. The regulatory risk assessment is under development and will be available in due course.

The WWF Biodiversity Risk Filter Methodology Documentation

This document describes the underlying methodology of the Inform, Explore and Assess Modules that have already been integrated in the WWF BRF tool, including a description of the risk assessment framework, underlying structure, data and limitations. In addition, WWF and Climate & Company developed guidance that has not been included into the WWF BRF tool at this point: Guidance A, B and C. Guidance A and B, on the one hand, provide support for companies and financial institutions on collecting the required input data for the WWF BRF and WRF Assess Modules. Guidance A supports financial institutions with collecting location-specific proxy data on companies' operational sites. Guidance B supports companies and financial institutions with collecting location-specific proxy data on supply chain sites. On the other hand, Guidance C provides support for financial institutions on how the location-specific output data from the WWF BRF and WRF Assess Modules can be further processed and aggregated to the company- and portfolio-level. Figure 3 summarises the four components of the WWF BRF Methodology Documentation.

Figure 3: Overview of the components of the WWF BRF Methodology Documentation

BRF METHODOLOGY	**WWF BRF methodology:** Details the underlying methodology of the WWF BRF tool, including a description of the risk assessment framework, underlying structure and data and limitations.
GUIDANCE A: COMPANY DATA	**Guidance on location-specific company data:** Since location-specific company data is required to run the WWF BRF (and WRF) Assess Module, this guidance provides financial institutions with an overview of existing proxy data for company locations and how to collect and prepare them at scale.
GUIDANCE B: SUPPLY CHAIN DATA	**Guidance on location-specific supply chain data:** Since location-specific supply chain data is required to run the WWF BRF (and WRF) Assess Module, this guidance provides companies and financial institutions with an overview of existing approaches to collect and prepare location-specific supply chain data at scale.
GUIDANCE C: AGGREGATION	**Guidance on WWF BRF and WRF tools output:** Since the WWF BRF (and WRF) provide an assessment at the site level but not at the company or portfolio level, this guidance provides financial institutions with a description of how the output of the tools can be further processed and aggregated to the company and portfolio level.

To show how the WWF BRF tool can be applied to a representative investment portfolio using Guidance A and C, a case study was conducted on more than 600 companies listed in the MSCI All Country World Index (MSCI ACWI)[3] and operating across 24 WWF Risk Filter industry sectors (see WWF and Climate & Company, 2023).

3 The MSCI ACWI world index comprises 2,933 companies from 23 developed and 23 emerging markets. For more information, see *www.msci.com/our-solutions/indexes/acwi*.

2. COVERAGE AND ANALYTICAL FOCUS

Coverage of biodiversity-related risks

The current version of the WWF BRF covers **physical and reputational biodiversity-related risks that affect the locations of company or supply chain sites:**

- **Physical risks** are driven by the ways in which a business and its supply chains depend on and can be affected by both natural and human-induced conditions of land- and seascapes, and how pressures might deteriorate ecosystem services in the future. The global decline of ecosystem services, for example, could lead to reduced productivity (e.g., lack of fertile soils and pollination) or increased costs of inputs (e.g., scarcity of natural fibres or harvest losses).
- **Reputational risks** can result from a company's actual or perceived negative impacts on biodiversity and people. Reputational risk represents stakeholders' and local communities' perceptions of whether companies conduct business sustainably or responsibly with respect to biodiversity and can ultimately affect brand value and market share, among other factors. Adverse effects on business could emerge from, for example, damages to the corporate brand and thus declining sales, or greater investor scrutiny and thus declining share price.

Additional biodiversity-related risks, such as regulatory (i.e., policy and legal) and market risks, as well as an assessment of biodiversity-related opportunities, are under development and will be added in due course.

This classification of risks aligns with the risk classification of the Taskforce on Nature-related Financial Disclosures (TNFD), according to which biodiversity-related risks can be classified into physical, transition and systemic risks. Transition risks are further divided into policy and legal, market, technology and reputational risks (TNFD, 2022b).

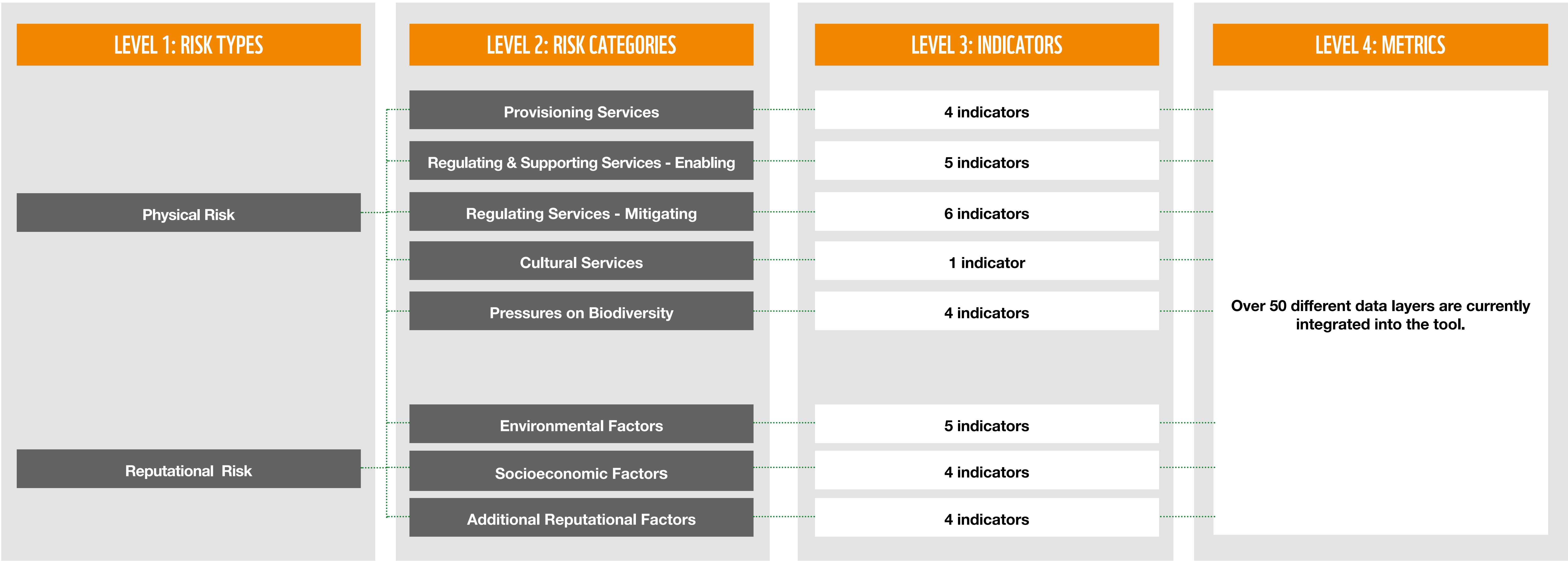
To assess the different aspects of physical and reputational biodiversity-related risks, the WWF BRF follows a four-level risk hierarchy. It breaks down the physical and reputational risk into 33 different indicators (see Table 8 in the Appendix), covering aspects of biodiversity that may be (or may become) material risks from a financial or environmental and social perspective.

The risk hierarchy consists of the following four levels (see also Figure 4):

- **LEVEL 4,** Metrics, comprises the raw global data sets that measure different aspects of biodiversity and ecosystems in a specific location that may lead to biodiversity-related risks for companies and financial institutions. Currently, the WWF BRF tool contains 56 global biodiversity data sets;
- **LEVEL 3,** Indicators, comprises information on the importance and local integrity of biodiversity aspects, not as raw data but spatially (dis-)aggregated to an assessment unit and translated to a risk score ranging from 1 to 5. The 56 metrics currently integrated in the WWF BRF have been grouped into 33 indicators (20 physical risk and 13 reputational risk indicators);
- **LEVEL 2,** Risk categories, groups the indicators into higher-level risk clusters with more direct relevance to companies and financial institutions. The 33 indicators have been grouped into eight different risk categories (five physical risk categories and three reputational risk categories); and
- **LEVEL 1,** Risk types, combines the risk categories into the broader risk types (physical risks and reputational risks).

It should be noted that risk types, risk categories and indicators are visible in the tool, but metrics (i.e., the raw data sets) are not.

Figure 4: WWF BRF risk hierarchy



This structure was, on the one hand, put in place to construct a hierarchical framework that consists of not only broad risk types, but more specific risk categories, as they provide more insights on the aspects the risks are comprised of. For example, biodiversity-related physical risks comprise very different aspects of biodiversity, ecosystems and their services. In this case, the availability of "Provisioning Services" (such as wood or fibre) can be investigated separately from the availability of "Regulating and Supporting Services" (such as pollination or soil condition). On the other hand, these broad risk types (i.e., physical and reputational risk) and the general structure of the WWF BRF risk hierarchy have already been successfully used in the WWF WRF. This ensures consistency between water- and biodiversity-related risk assessments and offers users a familiar approach that is still specific to the topics of water and biodiversity.

The WWF BRF provides an assessment of biodiversity-related risks taking into account industry sectors' dependencies on ecosystem services *and* impacts on biodiversity. Still, it is not a biodiversity footprint assessment that quantifies the negative impacts a company's or supply chain's operations might have on biodiversity. It is also not a comprehensive model of biodiversity-related risks to nature and people. It is a user-oriented model of biodiversity-related physical and reputational risks to companies and financial institutions. It supports them to prioritise what and where to act and better identify material biodiversity-related risks.

Coverage of industry sectors

The WWF BRF provides an assessment of 25 industry sectors, encompassing the full spectrum of corporate activity. The 25 industry sectors were defined based on a harmonised list of different standard industry classifications. Existing standard industry classifications were narrowed-down to this list of 25 WWF Risk Filter industry sectors since some broader Global Industry Classification Standard (GICS) classifications (e.g., electric energy production) face diverse biodiversity-related risks and therefore are better served through disaggregation (e.g. into electric energy production from solar/wind; hydropower; combustion; etc.), while others facing similar biodiversity-related risk (e.g., professional services; software; etc.) need not be disaggregated and were therefore grouped into the same category. Table 6 in the Appendix contains an overview of all corporate activities or processes that are associated with each WWF Risk Filter industry sector.

Therefore, the WWF BRF can be applied by companies from all industry sectors and to a broad portfolio of companies.

Coverage of asset classes

The WWF BRF tool offers a biodiversity-risk assessment based on the industry sector classification and the importance and local state of biodiversity integrity. As biodiversity aspects are highly variable across geographies, location-specific company data (i.e., location of company sites, industry classification and business importance of the site) is required to run the WWF BRF Assess Module. As location-specific company data is not always readily available, especially for financial institutions and investors, Guidance A and B provide an overview on existing data sources that can be used in the absence of company-reported location-specific information. By downloading the results from the Assess Module (available via a downloadable Excel function) and using the WWF and Climate & Company Guidance C, the results can be further aggregated to the company- and portfolio-level. Against this background, all asset classes directly related to companies (e.g., private and listed equity, corporate bonds, real estate or other tangible assets) can be analysed.

3. HOW TO READ THIS DOCUMENT

The WWF BRF Methodology Documentation is structured according to the four implementation steps one needs to follow to perform a risk assessment with the WWF BRF or WRF, presented in Figure 5.

Figure 5: Overview of implementation steps to run the WWF BRF or WRF Assess Modules

STEP 0: SCOPING THE ASSESSMENT

The WWF BRF and WRF tools' Inform Module and Explore Modules can help focus the scope of the assessment on priority industries and geographies as recommended by TNFD and SBTN.

BRF INFORM MODULE

Step 0A: Identifying industry materiality

The WWF BRF Inform Module provides information about the level of dependencies on ecosystem services and impacts on biodiversity for a total of 25 industry sector.

BRF & WRF EXPLORE MODULE

Step 0B: Exploring biodiversity and water importance and integrity

The WWF BRF and WRF Explore Modules provide maps showing the level of risk worldwide based on a total of 33 biodiversity risk indicators and 32 water risk indicators.

STEP 1: COLLECTING LOCATION-SPECIFIC COMPANY AND SUPPLY CHAIN DATA

After refining the scope of the assessment in Step 0, collect location-specific data on (portfolio) companies' operational and supply chain sites. The following input data is required to use the Assess Modules of the WWF BRF and WRF tools:

- Geographic location of sites (coordinates or address)
- Industry classification of sites (using WWF Risk Filter industry sector classification)
- Business importance of sites (indicated through high, medium or low importance)

GUIDANCE A: COMPANY DATA

For financial institutions

As a majority of financial institutions do not currently have easily available location-specific company information, WWF and Climate & Company developed guidance on how to collect location-specific proxy data for portfolio companies at scale.

GUIDANCE B: SUPPLY CHAIN DATA

For companies and financial institutions

As a majority of companies and financial institutions do not currently have easily available location-specific supply chain information, WWF and Climate & Company developed guidance on how to collect location-specific proxy data for supply chains at scale.

Biodiversity Risk Filter

Data input

Water Risk Filter

STEP 2: ASSESSING BIODIVERSITY-RELATED RISKS

The Assess Module combines the sites' industry materiality rating (0A) and the local biodiversity importance or integrity rating (0B) into a scape risk score for each company location. This comprises 33 biodiversity indicators from "water scarcity" to "terrestrial modification" following the BRF risk hierarchy.

Industry Materiality (0A)

BRF INFORM MODULE

Biodiversity integrity (0B)

BRF EXPLORE MODULE

Biodiversity risk score (2)

BRF ASSESS MODULE

STEP 2: ASSESSING WATER-RELATED RISKS

See WWF Water Risk Filter Methodology.

Data Output

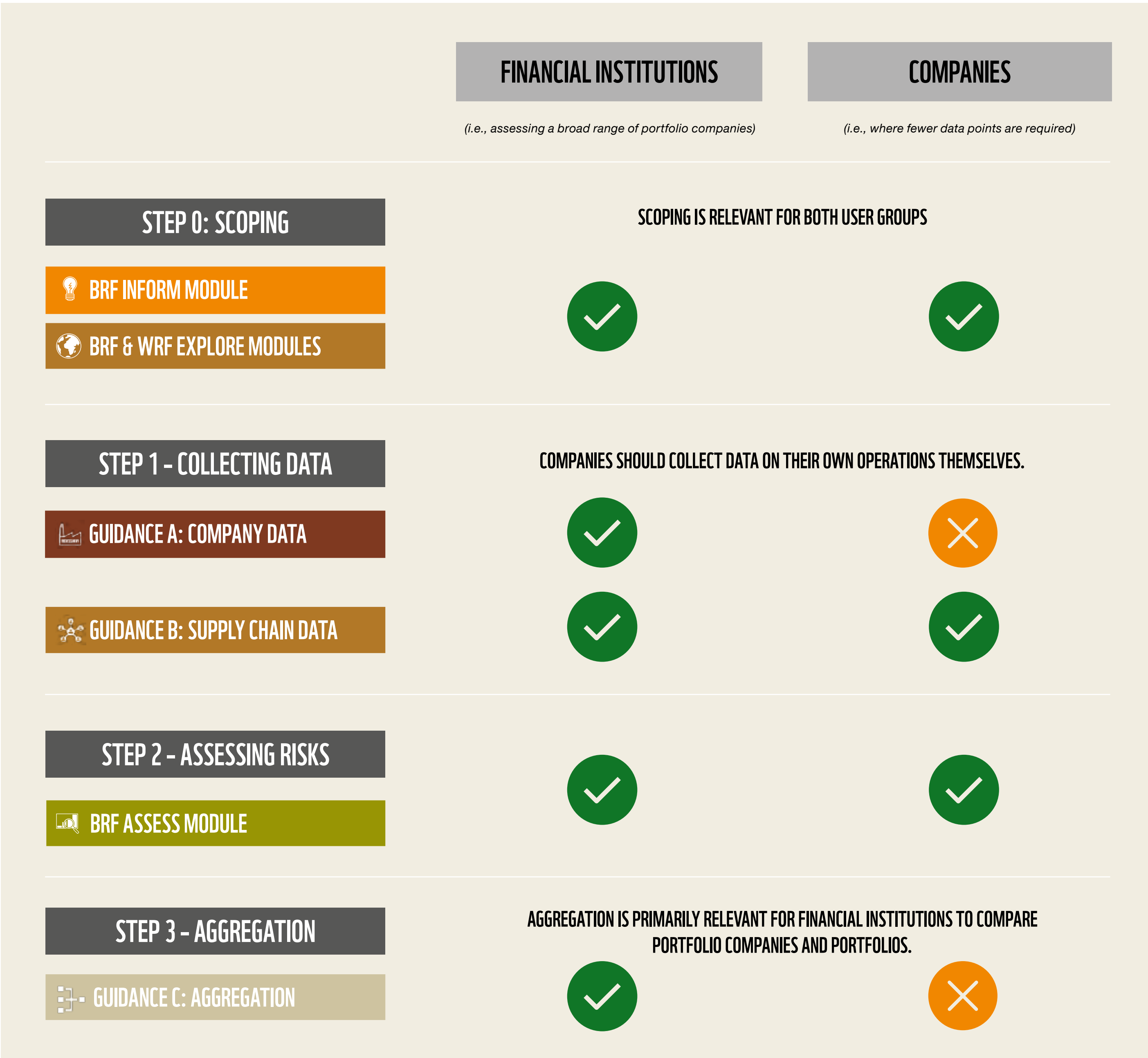
STEP 3: AGGREGATING BIODIVERSITY RISK TO THE COMPANY AND PORTFOLIO LEVEL

GUIDANCE C: AGGREGATION

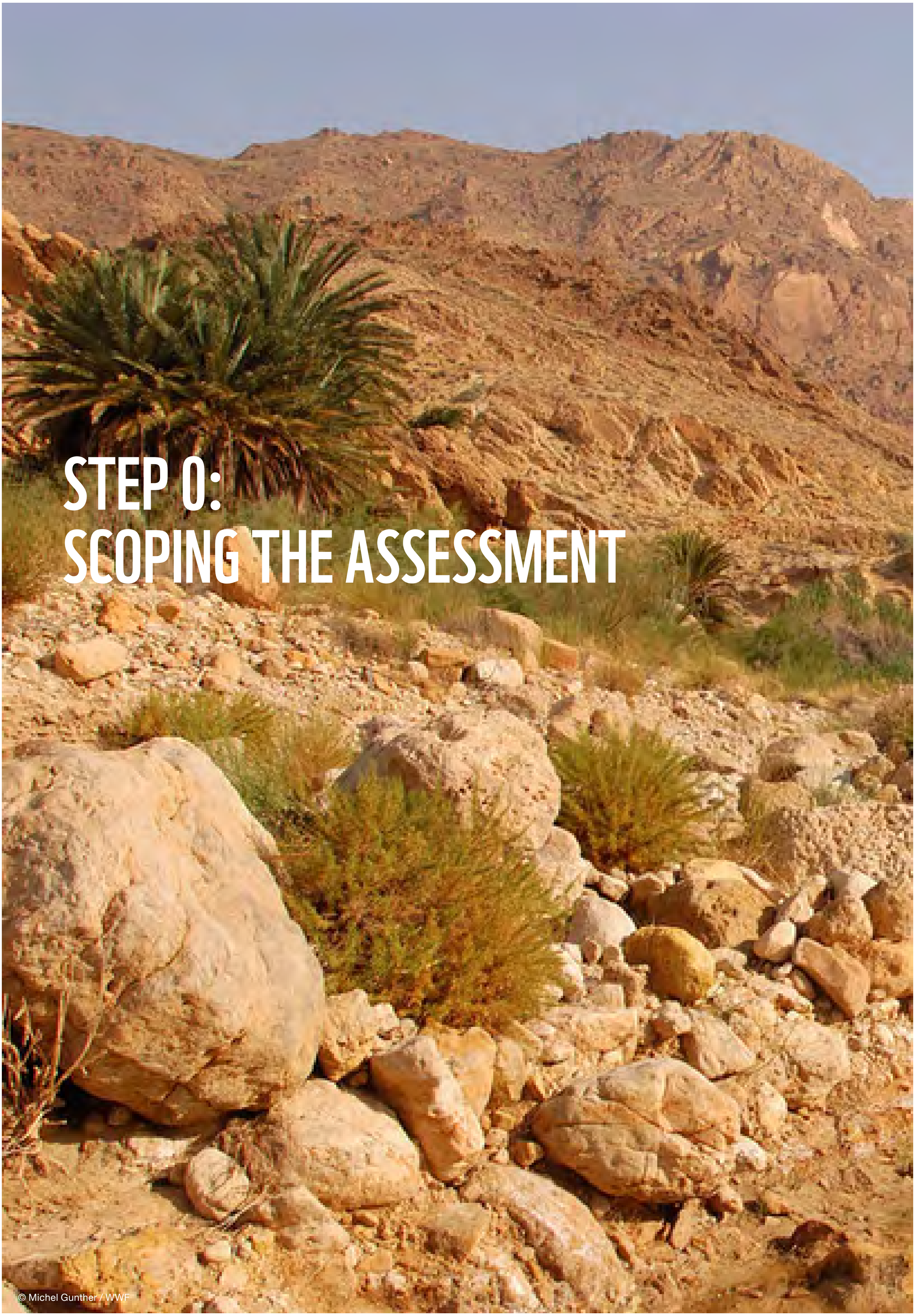
For addressing the needs of financial institutions, WWF and Climate & Company developed guidance on how to aggregate scape risk per indicator to the company and portfolio level using the site-specific WWF BRF data outputs. While this guidance focuses on biodiversity risk, the same aggregation approach can be applied with the outputs of the WWF WRF data outputs.

Since different user groups (e.g., companies, banks, asset managers, insurance companies, development banks) have different access to the required location-specific input data and are interested in results on different levels (e.g., site-, company-, portfolio-level), not every step is equally relevant for the respective user. Figure 6 provides an overview of the relevant implementation steps per user group and broadly distinguishes between financial institutions and companies. By financial institutions, we refer broadly to financial entities interested in assessing a wide range of (listed or unlisted) companies and their respective sites. Financial institutions interested in assessing a single company or project should follow the suggested steps for companies and not rely on proxy data.

Figure 6: How to use the WWF BRF Methodology Documentation per user group



STEP 0:
SCOPING THE ASSESSMENT



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Companies and financial institutions are recommended, especially if the topic of biodiversity is relatively new to the organisation, to define a narrowed-down scope before starting with the biodiversity-related risk assessment. The scoping aims to familiarise oneself with the approach of biodiversity-related risk assessment, build a better understanding of it and reduce the complexity at the beginning. Once familiar with the approach, organisations should extend the depth and breadth of the assessment, as a comprehensive assessment of biodiversity-related risks requires the inclusion of the companies' operational sites and (upstream and downstream) supply chain sites.

TNFD (2022b) and Science Based Targets Network (SBTN) (2020a), for example, provide companies and financial institutions with a specific set of questions that support them in narrowing down the scope of the assessment. For companies, these include considerations on what business operations can reasonably be considered (e.g., direct operations, supply chain operations) based on internal and supply chain data and what biodiversity aspects can and should be considered from a double materiality perspective (i.e., biodiversity aspects imposing a risk to the business and corporate activities imposing a threat to biodiversity). For financial institutions, these include considerations on the type of business of the financial institution (e.g., credit operations for banks; equity investment for asset managers; project finance for development banks; etc.), which industries and geographies capital is predominantly allocated to and where and how their financial activities interact with biodiversity. An output of the scoping assessment could be an initial heat map of the priority industries and geographies.

The WWF BRF Inform Module and Explore Module can support companies and financial institutions to focus the scope of the assessment on priority industries and geographies:

- **The WWF BRF Inform Module** helps to narrow the assessment from an **industry perspective** by providing information about the level of dependencies on ecosystem services and impacts on biodiversity for a total of 25 industry sectors encompassing the full spectrum of corporate activity. This helps to identify the company activities or the industry sectors with the highest impact or dependency.
- **The WWF BRF Explore Module** helps to narrow the assessment from a **geographical perspective** by providing maps on the importance and integrity of biodiversity, showing the level of biodiversity risk worldwide based on a total of 33 biodiversity indicators. This helps to identify biodiversity-related hotspot locations.

The following sections explain the WWF BRF Inform Module (Step 0A: Identifying industry materiality) and Explore Module (Step 0B: Exploring biodiversity importance and integrity) in more detail.

STEP 0A: IDENTIFYING INDUSTRY MATERIALITY (INFORM MODULE)

Since corporate activities impact biodiversity and depend on ecosystem services to different degrees, industry impact and dependency materiality ratings were developed for all 25 WWF Risk Filter industry sectors, encompassing the full spectrum of corporate activity (see Table 6 in the Appendix). For each of the 25 industry sectors, a dependency and/or impact rating was assigned to each of the 33 indicators of the BRF risk hierarchy, resulting in a total of 825 industry-indicator pairs. The rating was performed on a scale from 1 to 5: an industry materiality of 5 indicates a very high dependence or impact on the specific indicator, while an industry materiality of 1 indicates a very low dependence or impact. If an industry has no dependence or impact on a specific indicator, an industry materiality rating of 0 was assigned.

For example, the WWF Risk Filter industry sector 'Agriculture (plant products)' has a dependency rating of 5 for the physical risk indicator 'Soil Condition', indicating that agricultural plant production heavily depends on healthy soils. It has a dependency rating of 0 for the physical risk indicator 'Limited Marine Fish Availability', as there is no direct relationship to that indicator, and it has an impact rating of 5 for the reputational risk indicator 'Protected/Conserved Areas', indicating that agricultural activities may be very harmful, if they overlap with protected/conserved areas (see Table 9 in the Appendix).

The definition of the industry materiality ratings for the assessment of the dependencies was based on work conducted by ENCORE (2022), and for the assessment of impacts, it was based on the work by SBTN (2020a). The industry materiality ratings were slightly adjusted following peer reviews with WWF experts, financial institutions and companies. The ratings have been adjusted to enable a comparison between industry sectors and allow for a meaningful aggregation of the indicator scores to risk categories and types.

That means that while the industry materiality ratings are meaningful within the context of the WWF BRF risk assessment, they should not be taken out of the context of the WWF BRF. Table 7 in the Appendix contains an overview of all 825 industry materiality ratings for the 25 WWF Risk Filter industry sectors. These can also be seen, explored and downloaded in the WWF BRF Inform Module.

The industry materiality ratings provide a first overview of the level of the materiality of different industries to biodiversity-related risks covered in the WWF BRF. It helps users understand how different corporate activities might impact biodiversity or depend on ecosystem services to varying degrees. It subsequently allows users to assess highly material issues or parts of the supply chain representing highly impactful or dependent industry sectors.

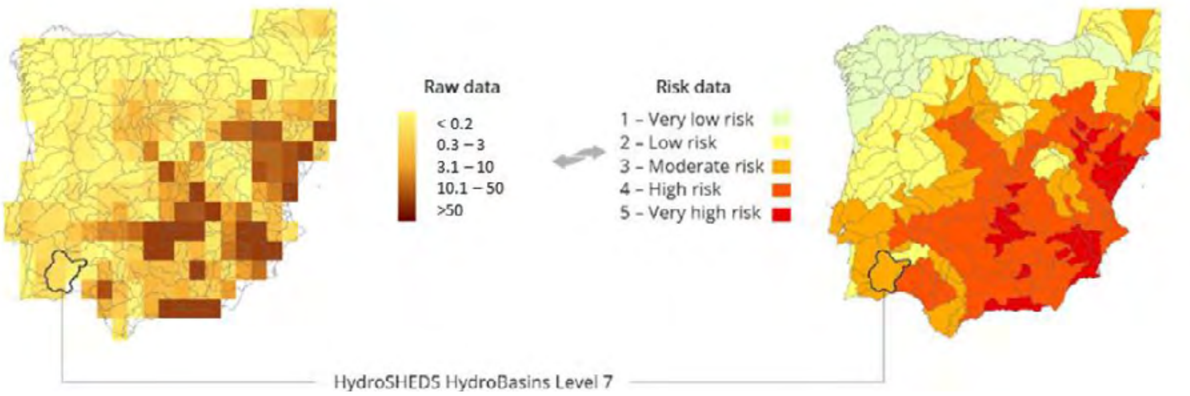
STEP 0B: EXPLORING BIODIVERSITY IMPORTANCE AND INTEGRITY (EXPLORE MODULE)

The biodiversity importance and integrity assessment are based on the 56 global data sets that inform the WWF BRF's indicators (LEVEL 3 of the WWF BRF risk hierarchy). Each data set represents an evaluation of the importance or state of biodiversity integrity in a specific land- or seascape.

To produce indicators, it is necessary to adapt the raw data sets in two ways:

- **Alignment of spatial scales:** the data sets use a variety of spatial scales (e.g., on a country level; 30m x 30m; etc.). So, the raw data first needed to be spatially aggregated or transposed to a common scale. For terrestrial areas, the WWF BRF follows the WWF WRF assessment unit to the level of HydroSHED Level 7 (Lehner & Grill, 2013) as this represents a degree of functional coherence at a biodiversity-level. For marine areas, the WWF BRF uses *Marine Ecoregions of the World (MEOW)* for coastal areas and *FAO Major Fishing Areas* for the high seas.
- **Translation of raw data to risk score classes:** The data sets provide data in a variety of different units. So, the raw data was translated into the five risk score classes (i.e., given a value from 1 to 5). This normalisation process (see Figure 7) allows for easy comparison between indicators and allows indicators to be aggregated with others.

Figure 7: Normalising raw data

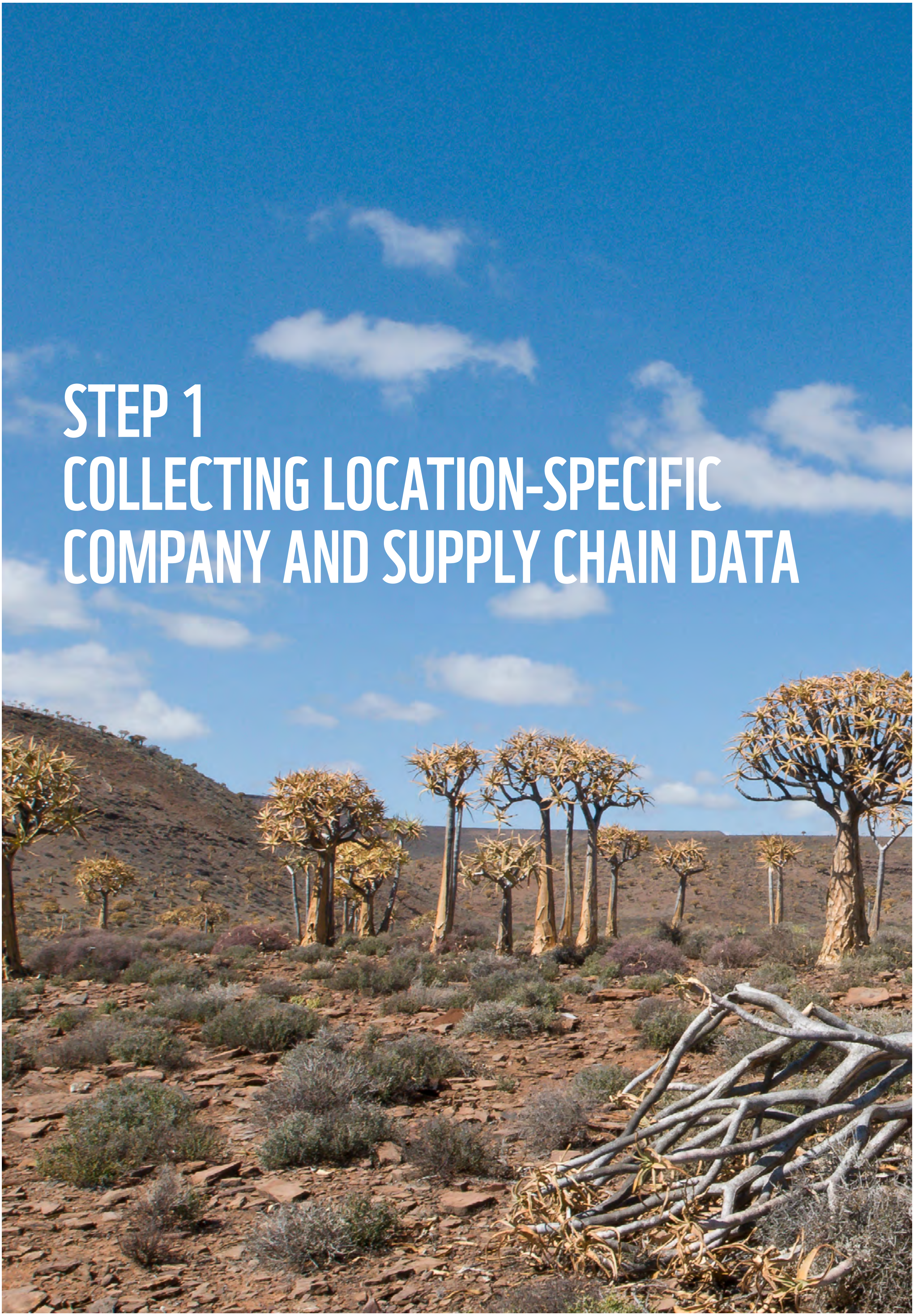


A risk score of 5 indicates very high risk, while a score of 1 indicates very low risk. If there was no data for an indicator at a specific location, a risk score of 0 was assigned. Thresholds between risk score classes were chosen individually for each data set. Details on the data source, adaptation steps and translation into the five risk score classes can be found in Appendix 0.4. The resulting global maps for the indicators, risk categories and risk types can be found in the WWF BRF Explore Module.

It should be noted that the WWF BRF is based on the best available data sets. While data sets are updated on a regular basis, the WWF BRF is not intended to provide an assessment of real-time biodiversity-related risk conditions.

The global maps of biodiversity importance and integrity provide a first overview of the level of biodiversity risk aspects covered in the WWF BRF. They help the user to understand and identify biodiversity-related hotspots and areas of key biodiversity importance and subsequently allow to focus the assessment on high-risk geographies.

STEP 1
COLLECTING LOCATION-SPECIFIC COMPANY AND SUPPLY CHAIN DATA



Biodiversity-related dependencies and impacts represent sources of risk for companies and financial institutions, as they affect business continuity, earnings and, ultimately, enterprise value. As the importance and state of biodiversity integrity vary from location to location, the biodiversity-related dependencies and impacts need to be assessed in a location-specific manner. Therefore, collecting data on where the (portfolio) company's operational and supply chain sites are located is crucial to incorporate the importance and integrity of biodiversity at a specific location into the analysis (TNFD, 2022b).

Required input data for WWF BRF Assess Module

Using the WWF BRF Assess Module to analyse biodiversity-related risks stemming from (portfolio) companies' **operational or supply chain sites** requires collecting the following input data:

- **Location of company operational sites and supply chain sites** (latitude, longitude): A company site designates a location where corporate activities are conducted. A portfolio of company sites should capture a business model in its entire complexity. This can include, for example, the extraction of resources, the manufacturing of goods (factories), the storage of items (warehouses), the sale of goods (retail or wholesale stores) or other professional activities (offices). The location of the company and supply chain sites helps to identify the interface of economic activity with biodiversity. Using the WWF BRF Assess Module requires collecting the coordinates (latitude, longitude) or the address of the company and supply chain sites.
- **Industry classification per site** (using WWF Risk Filter industry sector classification): Industry classifications place economic activities into industry groups based on similar production processes or similar products or services. This helps to make use of well-structured industry materiality ratings to understand how a specific economic activity depends on or impacts biodiversity. Using the WWF BRF Assess Module requires a classification of industries according to the WWF Risk Filter industry sector classification (see Table 6 in the Appendix). Therefore, crosswalks for widely used industry classification standards are required.[4]
- **Business importance of a site** (indicated trough high, medium or low): The business importance describes the relative importance of a site to the overall company (e.g., a site with 5,000 units of output per year might be more important than a site with only 1,000 units of output). Therefore, to better understand organisation-wide implications, the business importance of each location-industry pair must be identified. This is conceptually challenging as the business importance can vary for many reasons (such as distinct spatial characteristics; the production of unique products; high importance for customer relationships; etc.). Whenever possible, making use of expert opinion and industry knowledge is suggested to determine the importance of a site. Using the WWF BRF Assess Module requires the user to select the importance according to three categories: high, medium or low importance.

Users can manually enter the required input data into the WWF BRF tool via a mask within the tool or upload it via the provided ***Excel template on the WWF Risk Filter Suite Platform.***

Required additional data for company- and portfolio-level aggregation (Guidance C)

For companies and financial institutions who would like to deploy Guidance C (i.e., aggregating biodiversity risk to the company and portfolio level), the following additional data points are required:

- **Numeric weights for the business importance of each site:** Guidance C for financial institutions describes how to derive numerical values for the importance per site (summing up to 1 at the company level). This is required for aggregating the risk scores at the company level (see Step 3a).
- **Portfolio weights per company:** For financial institutions, the weight per portfolio company serves as a weighting factor to derive portfolio-level aggregation.

4 We refer here to widely used industry classifications such as the North American Industry Classification System (NAICS), the Bloomberg Industry Classification Standard (BICS), the Global Industry Classification Standard (GICS) developed by MSCI and Standard & Poor's, the classification system of the European Community, abbreviated as NACE, or the International Standard Industrial Classification of All Economic Activities (ISICs). If these are used by the user internally, they need to be mapped to WWF Risk Filter industry sector classification. As this consist of only 25 larger macro sectors, creating a crosswalk is relatively simple.

Another data point is needed to process and aggregate the analysis of supply chain sites (see Step 3C). Conceptually speaking, the biodiversity-related supply chain risk score per risk type, ***r***, of a Firm, ***A***, is the sum of the first-order risk scores per risk type (physical or reputational) of all ***n*** suppliers, weighted by a weighting factor, ***w***, per supplier, ***i***, which denotes the importance of the supplier-customer relationship: [5]

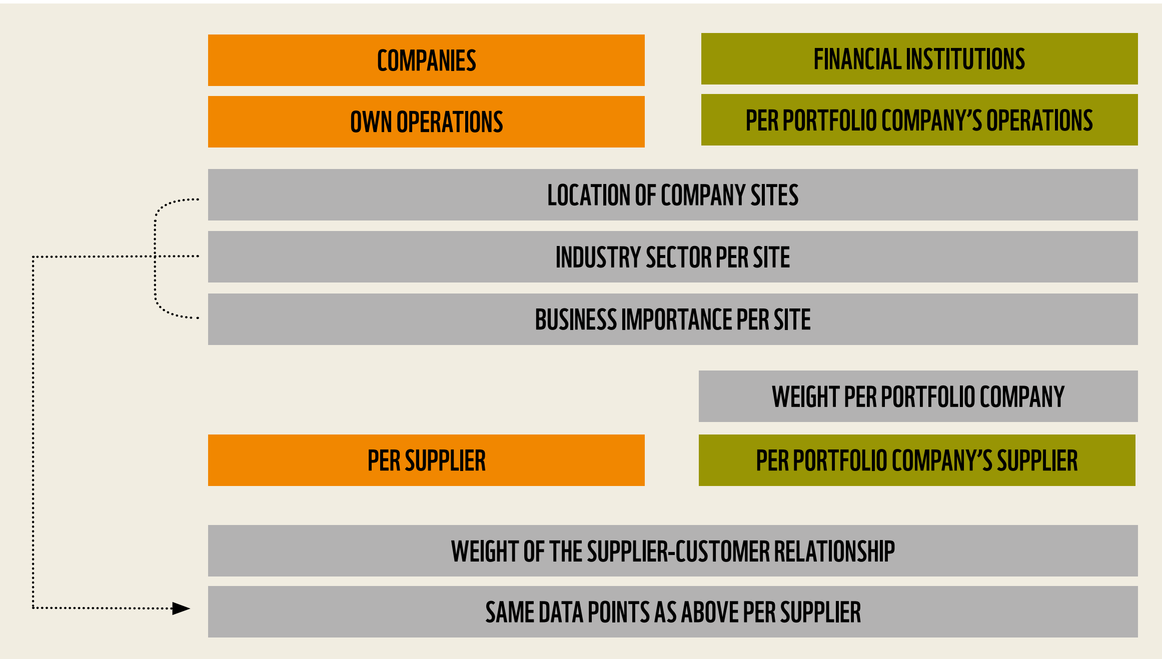
$$\textit{Supply Chain Risk Score}_{A,r} = \sum_{i=1}^{n} w_i \times \textit{1st order risk score}_{r,i}$$

Aggregating the supply chain dimension, requires the following additional data point per (portfolio) company's supplier next to location-specific supplier data (i.e., location of supply chain sites, industry classification and business importance of site):

- **Supplier-customer relationship:** To distinguish between important and less important suppliers for the company of interest, information on the supplier-customer relationship is needed. This could be, for example, the revenue dependent on the supplier-customer pair.

This results in different data requirements subject to the user group and scope of the assessment (see Figure 8).

Figure 8: Required input data per user group (company vs. financial institution) and scope (own vs. supply chain sites)



Availability of required input data

For individual companies, most of the required input data typically exist in their data infrastructure and collection process. Thus, individual companies should collect and prepare the required location-specific data for their operational sites themselves instead of relying on proxy data (since companies are data issuers, compared to data users (TNFD, 2022c)). This data should be relatively quick for companies to collect and prepare in a format acceptable to the WWF Risk Filter Suite tools. However, location-specific data on the company's suppliers are often not yet part of companies' data infrastructure and collection processes and must therefore be collected additionally. Guidance B illustrates how input-output (IO) models can be of use in collecting these data. However, we strongly suggest that companies engage their key suppliers on the location-specific data required before relying on IO models, as data received directly from the supplier increases the accuracy of the assessment.

5 This formula is largely a conceptual explanation and contains questionable assumptions (such as that risks are distributed linearly across suppliers). The relevant subchapter, Guidance B goes into more depth on the limitations of the supply chain analysis presented.

For financial institutions, the required location-specific data for a broad range of portfolio companies' operational sites and supply chain sites is typically not part of their data infrastructure and collection process and must therefore be collected additionally. As the required data are often not reported by companies, Guidance A explains how location-specific information on companies' operational sites can be collected at scale using existing data solutions and proxies (e.g., asset-level data sets; corporate structure data sets; etc.). However, we strongly suggest that financial institutions collect the required location-specific data directly from their portfolio companies to increase the accuracy of the assessment. As for companies, Guidance B provides support in assessing the supply chains of the portfolio companies.

Given the above mentioned difficulties in the data collection and preparation process, WWF and Climate & Company developed additional methodological guidance for companies and financial institutions which are presented in the following subchapters:

- Guidance A: Collecting location-specific proxy data on portfolio companies' operational sites
- Guidance B: Collecting location-specific proxy supply chain data

GUIDANCE A: COLLECTING LOCATION-SPECIFIC PROXY DATA ON PORTFOLIO COMPANIES' OPERATIONAL SITES

Guidance A explains which available data sources can be used by financial institutions as proxies for the required location-specific information on portfolio companies' operational sites (i.e., location of company sites, industry classification and business importance of the site). In total, four potential data sources were identified and analysed that could serve as proxies in the absence of corporate disclosure:

- **Corporate disclosure data** refers to location-specific information reported by companies directly to the financial institution or publicly. Ideally, financial institutions obtain the required location-specific company data from corporate disclosures, as these have the highest quality and accuracy. However, these data points still need to be systematically disclosed.[6]
- **Asset-level data** refers to data about physical assets, including attributes such as coordinates, asset type, production capacity, productivity and age, tied to ownership information. Commercial and open-source data providers typically offer this data (such as Asset Resolution or the Spatial Finance Initiative (SFI)).
- **Corporate structure data**, also referred to as corporate hierarchy or corporate ownership structure data, is typically a by-product of commercial data providers (e.g., Bloomberg or FactSet). It links the ultimate parent company to its subsidiaries, affiliates and assets, including information on their industry classification and location.
- **City of headquarters data** refers to location-specific information on a company's headquarters (i.e., location and industry classification) and are available in commercial data sets. This implies that each company is assessed on only one location.
- **Disaggregated revenue data** refers to revenue reporting by country (e.g., Firm A generates 20 per cent of its revenue in country X) and by industry (e.g., Firm A generates 10 per cent of its revenue in industry Y). This data is provided by commercial data providers (such as Refinitiv, Bloomberg or FactSet).

Next to the individual data sources, also a hybrid approach was investigated:

- **Hybrid approach** refers to a combination of different data sources that have been identified as potential proxies for company-reported location-specific information. As all data sources identified have different advantages and disadvantages, combining them in a hybrid approach offers the possibility to use the strengths and reduce or avoid the disadvantages of the individual data sources.

6 Corporate disclosure data is not investigated further, as this guidance focuses on proxy data in the absence of corporate disclosure on location-specific company data.

The following subchapters introduce the different proxy data sources and the hybrid approach in more detail and discuss their coverage, advantages and disadvantages (see also Table 12 in the Appendix) and the available data points to approximate the required WWF BRF (or WRF) input data. The subchapters also contain workarounds in case typical data challenges, such as missing values, occur. The data sources are presented in the order of suggested priority for data gathering (see also Figure 9).

Figure 9: Analysed data sources

1. HYBRID APPROACH

While this is not an off-the-shelf data source, this approach suggests combining multiple data sources rather than relying on only one to use each data source's advantage and increase coverage of location-specific company information (see Box 1 for an example).

Coverage: Subject to the number of combined data sources and sets, this approach has the most extensive and granular coverage of industry sectors.

Advantages: Combining multiple data sources and sets addresses the various disadvantages of each data source and leverages their advantages. In addition, industry sectors not covered in a particular data set can be replaced by another. For example, combining different industry-specific asset-level data sets (focusing on production facilities) with corporate structure data (containing other entities and subsidiaries linked to the parent company) reduces the data-cleaning process and increases the depth and coverage of industry sectors (see Box 1).

Disadvantage: Processing, cleaning and merging different data sources to build a comprehensive location-specific data set can be time-consuming and costly, especially if the organisation does not yet have access to the data sets. Determining the business importance of each site is also methodologically more challenging, as different data sources contain different data points that could be used as a proxy for business importance.[7]

Recommendation: If capacity is available, we suggest merging different data sources. Apart from implementation costs, this approach yields the most comprehensive list of location-specific data points as it does not rely on only one data source and can thus fill in missing data points.

7 Example: Production facilities retrieved via asset-level data may contain information on the facility's size in terms of annual production capacity. Subsidiaries retrieved from corporate structure data (not necessarily a production plant) may not include this information.

BOX 1:
A HYBRID APPROACH – COMBING ASSET-LEVEL DATA WITH CORPORATE STRUCTURE DATA

Data sources can also be combined for more comprehensive coverage and to reduce or avoid the disadvantages of individual data sources. Below, an example of the hybrid approach is presented using the example of a cement company called Company A.

Collecting location-specific company data via asset-level data sets

The SFI data set yielded 138 production facilities for Company A, containing information about the facilities' location, ownership, capacity, production process and age. Therefore, all required input data for the assessment could be found clean and ready to use.

Collecting location-specific company data via corporate structure data

Downloading data from FactSet's Data Management Solution provided a list of 990 entities related to Company A. However, the quality of the location and industry sector information varied and required data cleaning:

- **Location of company sites:** 489 entities were dropped since no information on the location was given. 501 entities remained. For subsidiaries with location information at the city level, a spatial extrapolation approach was used to identify the respective coordinates.
- **Industry classification:** Regarding the industry classifications, Company A's subsidiaries were linked to a total of 63 distinct NACE codes (with around 20 per cent linked to finance). Only subsidiaries with an industry attribute linked to the official corporate revenue reporting were kept to eliminate locations not relevant to the business model. This yielded a list of 130 location-industry pairs in total.

Combining the two data sets

To merge both data sets, the asset-level data set (i.e., 138 production facilities) was combined with the locations from the corporate structure data set, which were not part of the asset-level data set (i.e., subsidiaries fulfilling other functions). This improved the number of locations associated with Company A and provided a more complete picture of Company A and its various economic activities.

2. ASSET-LEVEL DATA

Coverage. A range of asset-level data sets have been compiled by commercial and open-source data providers, mostly covering economic activities related to the energy, transport (automotive and aviation) and manufacturing (steel, cement, etc.) industries. Commercial providers reach the largest asset coverage of assets. However, there are still apparent data gaps, particularly from a biodiversity perspective, as high-impact industry sectors such as agriculture and forestry are often not covered (see Table 10 and Table 11 in the Appendix for an overview of the industry sectors covered). Nevertheless, asset-level data sets are expected to expand their scope to other industries, such as beef production and pulp and paper. Appendix Guidance A contains a non-exhaustive but comprehensive overview of available asset-level data sets from commercial and open-source providers.

Advantages. To assess biodiversity-related risks, it is important to know where assets are located, what sectoral attributes they have, and to whom they belong. This is precisely the information that asset-level data sets contain. Asset-level data can be easily aggregated at the company or portfolio level, allowing an objective, 'bottom-up' approach to measuring biodiversity-related risks. Furthermore, asset-level data sets focus on production facilities, power plants and extractives (instead of, for example, offices) that have high relevance for nature and biodiversity.

Disadvantages. A general limitation of asset-level data sets is the industry sector coverage, as described above. Further, open-source data sets might be less frequently updated and can provide a false sense of completeness compared to commercial alternatives. However, commercial alternatives can be expensive. Subject to data quality, incorporating selected asset-level data sets into a financial institution's data infrastructure can be time-consuming: For example, if a unique company identifier to the parent company is missing, users must map companies via text-matching or do the work manually.

Recommendation: First, asset-level data sets focus on production facilities, power plants and extractives (instead of, for example, offices) that have high relevance for nature and biodiversity. Second, the important contextual attributes facilitate a bottom-up approach to measuring biodiversity-related risks. Subject to the available (financial) capacity, we suggest exploring the range of open-source providers (such as the Spatial Finance Initiative) or commercial providers (such as Asset Resolution).

Example on how to use asset-level data. Using data from the SFI, for example, allows users to quickly identify the required input data points for the WWF BRF (or WRF) Assess Module (see Table 1): The location of company sites is required as well as the industry sector classification, which can be retrieved directly from the SFI data set[8]; and the data on production capacity can be leveraged to define the business importance of a site to the overall company. Box 2 highlights how production capacity data can be used as a proxy for the business importance of sites and explains workarounds in the absence of production capacity data.

Table 1: Asset-level data excerpt (Source: Spatial Finance Initiative, Cement Data)

Company	Country	Location of company sites (lat, long)[1]	Production capacity[2] (in millions of tonnes)
Cement company*	Belgium	3.44,50.78	0.90
	Germany	12.03,49.21	<missing>[A]
	Bangladesh	90.52,23.71	<missing>[A]
	Germany	9.74,48.37	1.90
	Egypt	32.21,29.77	4.20

* Required input for the WWF BRF Assess Module; 1) Capacity data is useful to determine the business importance of each site to the overall company; A) Work-around required. To maintain a large sample size, missing values could be replaced by the median (see Box 2).

BOX 2: SUGGESTED WORKAROUND TO RETRIEVE THE BUSINESS IMPORTANCE OF A SITE FORM ASSET-LEVEL DATA SETS

To define the business importance of each site to the overall company, the following possibilities were identified, subject to the quality of the data received:

1. **Use production capacity as a proxy.** Asset-level data sets might contain data on the annual production capacity as a proxy for the size of the plant. The business importance, ***BI***, per site, ***i***, can then be derived using the formula below:

$$BI_i = \frac{ProductionCapacity_i}{\sum_{i=1}^{n} ProductionCapacity_i}$$

with BI_i = business importance of site i

2. **Equal weighting.** If the solution above is not applicable, and manual screening is not an option, an equal weighting approach can be followed:

$$BI_i = \frac{1}{N}$$

with BI_i = the business importance of site i; and N = the number of company sites identified.

However, as mentioned above, the business importance can vary for many reasons (such as distinct spatial characteristics; the production of unique products; a high importance for customer relationships; etc.). Whenever possible, we suggest making use of expert opinion and industry knowledge next to quantitative indicators such as production capacity.

8 Example – The Global Database of Cement Production Assets from the *Spatial Finance Initiative*: Cement production can be assigned to the WWF Risk Filter industry sector "Construction Material". The NACE equivalent would be 23.51 – Manufacture of Cement".

3. CORPORATE STRUCTURE DATA

Coverage. Many commercial providers provide data on companies' corporate structure. These data sets provide a list of subsidiaries, affiliates, bank branches, corporate assets and other entities for each parent company. They are available for a broad universe of companies across all industries. For example, FactSet provides corporate structure data on almost 50,000 publicly listed companies across all industries (given a total universe of around 60,000 publicly listed companies in the FactSet database). Table 9 in the Appendix compares the coverage of listed companies with corporate structure data. Other data providers, such as ORBIS, also collect and provide company structure data for small and medium-sized enterprises (SMEs), covering several million companies. Appendix Guidance A contains a non-exhaustive but comprehensive overview of available corporate structure data providers.

Advantages. The main advantages are the availability of the required data points (location of sites, industry classification and business importance) in a well-structured format, including company identifiers, allowing a smooth integration due to low implementation costs, and broad coverage of listed and non-listed companies. In addition, many financial institutions already have access to such databases.

Disadvantages. Since the data product focuses on the corporate structure, production plants might only be part of the data set if they belong to a separate legal entity (e.g., a subsidiary). Regarding coverage, company structure data sets yield data points for a broad range of companies. However, the number of sites per company can vary significantly (from several hundred sites to only one). This can give a false sense of completeness regarding the company sites covered. In addition, the quality of the data retrieved can vary. For example, location or industry classification data might be missing. Missing values require either workarounds or removal of company site from the data set.

Recommendation: This proxy is a great starting point due to its broad company coverage and low implementation costs. When using it, analysts should be aware of its limitations. Since the data product focuses on the corporate hierarchy, production plants might not be part of it when they do not belong to a separate legal entity (e.g., a subsidiary).

Example on how to use company structure data. Table 2 provides an example excerpt of corporate structure data and highlights which data points can be used for the WWF BRF (or WRF) Assess Module. Box 3 further provides guidance on workarounds in case of missing values for the location of sites, industry classification and business importance of the sites. For a more detailed discussion on the coverage of company structure data sets and a comparison of biodiversity risk analysis under asset-level and corporate structure data sets, see Appendix Guidance A: Case study – the importance of input data.

Table 2: Excerpt corporate structure data (Source: FactSet)

Company	Type	Location of company site	Industry classification (NACE)[A]
Cement company	Corporate asset	<missing>[B]	46.73 – Wholesale of construction materials
	Corporate asset	country	23.51 – Manufacture of cement
	Public company	106.81, -6.22	23.69 – Manufacture of other articles of concrete, plaster and cement
	Subsidiary	City[B]	<missing> [B]
	Subsidiary	24.69,59.41	<missing> [B]
	Subsidiary	<missing>[B]	<missing> [B]

A) The retrieved industry classification needs to be mapped to the WWF Risk Filter industry sector classification; B) Work-around required. Replace value with a reasonable assumption or drop observation (see Box 3).

BOX 3: SUGGESTED WORKAROUNDS TO RETRIEVE THE REQUIRED INPUT DATA (LOCATION OF COMPANY SITES, INDUSTRY CLASSIFICATION, BUSINESS IMPORTANCE) FROM CORPORATE STRUCTURE DATA SETS

Location of company sites: The quality of data regarding the location of company sites varies. The location is sometimes available in the form of precise coordinates, sometimes only for the city, region or country and sometimes not at all. We suggest approximating the geographical location if address, city or NUTS3 (Nomenclature of Territorial Units for Statistics) information is available. The European Central Bank has also followed this approach (ECB, 2021). To ensure the accuracy of the data, we suggest dropping observations for which the data provider specifies only the country, as this does not offer the required spatial granularity to incorporate the importance and local integrity of biodiversity.

Industry classification of sites: There can be missing industry values per subsidiary in the data sets. For data retrieved from FactSet's Data Management Solution (containing corporate structure data), we retrieved the subsidiaries for all publicly listed companies and for approximately 50 per cent of the subsidiaries no industry classification was given. In this case, the analyst needs to decide between 'drop or replace'. A standard method is to replace the missing value with the sample's mean or median (in this context: replacing the missing value of the subsidiary with the corporate's primary industry classification). Dropping an observation reduces the sample size, whereas replacing it might introduce a bias into the analysis (e.g., the subsidiaries might be related to industries with higher or lower dependencies/impacts).

Business importance of sites: To derive the estimated business importance of each site, three approaches were identified:

1. **'Size variables' per entity.** If possible, the user collects 'size factors' for each entity under scope to define the business importance of the site, $BI_{c,i}$, for company, ***c***, and site, ***i***, by dividing the size factor of the site, ***i***, by the sum of ***N*** size factors:

$$BI_{c,i} = \frac{Size\ factor_i}{\sum_{i=1}^{N} Size\ factor_i}$$

Size factors could be variables such as total assets, costs of goods sold, production capacities or other indicators that help to distinguish more material company sites from less material ones. However, we found very low coverage of 'size factors' for the (small) entities linked to the parent company. Unless the data availability changes or significant manual work is carried out, this solution remains impractical.

2. **Conditional assignment of the business importance of each site based on reported disaggregated revenue figures.** One of the main issues with corporate structure data is that the list of subsidiaries can contain industry sectors that do not show up in the corporate revenue reporting and are hence significantly less relevant for corporate business model. In the case of Cement Company A (see Box 1), for example, all subsidiaries retrieved via FactSet are associated with 63 distinct NACE codes, with 100 of them being linked to financial services (i.e., financing activities and not Cement Company A's main business activity). As a workaround, one can assign revenue conditionally based on reported revenue figures, which are available in most commercial data sets.

Example: Company A has 50 entities associated with industry sector X and 25 with industry sector Y. The revenue reporting tells us that Company A generates 80 per cent in industry X and 20 per cent in industry Y. For each company site assigned to industry X, we assign the value of 80 per cent/50. For each company site assigned to industry Y, we assign 20 per cent/25.

While this solution helps to filter out less relevant activities, revenue might not be the most accurate proxy since it focuses on revenue generation instead of production volumes and thus environmental materiality. For example, an apparel company might have its greatest environmental impact in the Global South, where the clothing is manufactured, rather than the Global North, where its products are sold and where most of its revenue is generated). Other variables reported by companies in disaggregated format are: assets, operating expenditures and capital expenditures (with varying quality).

3. **Equal weighting.** As with asset-level data, equal weighting can be applied: the business importance of site, $BI_{,i}$, for company, ***c***, and location, ***i***, is equally weighted according to the ***N*** entities under scope of company, ***c***:

$$BI_{c,i} = \frac{1}{N}$$

This approach is easy to implement but can be quite misleading without appropriate data cleaning. In the example of Cement Company A above, 20 per cent of business importance would be assigned to subsidiaries linked to financial services.

4. CITY OF HEADQUARTERS DATA

Coverage. While 'city of headquarters' is not a data product itself, it refers to the most basic company data that can either be collected manually or retrieved at scale from commercial data providers. This data is available for millions of listed and non-listed companies across the globe.[9] Orbis[10] could be a promising source, offering a database containing financial and business information on 116 million global public and private companies.

Advantages: The main advantage of such data is its availability and broad coverage of listed and non-listed companies. In limited cases, headquarter data may serve as a reasonable proxy, particularly for smaller firms with only one site.[11]

Disadvantages. It can provide a false sense of completeness if a company has several physical assets spread across the globe. The accuracy of this proxy relies on the assumption that most production is linked to the headquarter (putting aside the supply chain).

Recommendation: Only suggested as a backup option due to severe limitations. Even though the European Central Bank has used this proxy to run a large-scale risk assessment on millions of portfolio companies, the accuracy of the proxy relies on the assumption that 100% of the corporate production is linked to its headquarter.

BOX 4:
SUGGESTED WORKAROUNDS TO RETRIEVE REQUIRED INPUT DATA (LOCATION OF SITE, INDUSTRY CLASSIFICATION) FORM 'CITY OF HEADQUARTERS' DATA SETS

Location of company sites: Companies can be geolocated at the address level. If the precise address is not available, a spatial exploration approach can be used to assign proxy coordinates derived from companies' postal codes or nomenclature of territorial units for statistics 3 (NUTS3). This approach has been used by the European Central Bank in the context of its economy-wide climate stress test, in which the authors assessed each non-financial corporation to which a bank is exposed based on the entity's address level (ECB, 2021).

Industry classification of site: The primary industry classification can be retrieved from any commercial data provider.

9 For example, the European Central Bank conducted a climate stress test analysis on 4 million companies worldwide using information on their headquarters (ECB, 2021).

10 https://www.bvdinfo.com/en-gb/our-products/data/international/orbis

11 Unfortunately, this data proxy's (in)accuracy for smaller companies is unknown. Future research could investigate when smaller firms usually start expanding and operating in additional locations.

5. DISAGGREGATED REVENUE DATA

Coverage. Disaggregated revenue data sets are mostly available for listed companies and can be retrieved from a number of commercial data providers. For example, FactSet provides disaggregated revenue data for approximately half of the 60,000 listed companies it covers.[12] Table 9 in the Appendix compares the coverage of disaggregated revenue data sets with corporate structure data sets.

Advantages. Use of this data is common as the implementation costs are low due to its well-structured format. The data source has been used in different biodiversity-related risk assessment contexts. For example, biodiversity 'footprinting' tools, such as the Biodiversity Impact Analytics-Global Biodiversity Score, the Biodiversity Footprint for Financial Institutions and the Corporate Biodiversity Footprint, use revenue splits by country and industry sector as the starting point to link companies to models such as GLOBIO[13] to calculate companies' impact on biodiversity (WWF, 2021). For the assessment of upstream dependencies, Banque de France (2021) relied on similar data provided by Carbon4 Finance which provides the sectoral and geographical breakdown of revenue for each company (Carbon4 Finance, 2017).

Disadvantages. While disaggregated revenue data sets are relatively easily applied at scale, the most significant limitation is their limited spatial granularity. The country is the most granular spatial unit provided in these data sets which makes it difficult to accurately incorporate the importance and local integrity of biodiversity indicators into the analysis. A potential workaround could be to assess the land area-weighted average of an indicator at country level (for example, the average of biodiversity integrity in country X). This is also a (planned) functionality of the WWF BRF and WRF tools.[14] This approach clearly would work better with smaller countries and could be extremally misleading for countries with larger territories and/or high land use heterogeneity. Therefore, it is very important that the world's largest countries (at least Russia, Canada, United Stated, China, Brazil, Australia, India, Argentina, Kazakhstan and Algeria) are sub-divided into sub-national divisions (admin level 1) to avoid results being averaged across the climatic and land use variability to one value. Another major limitation is the homogeneity assumption: while we know in which countries and industries revenue is generated, the precise distribution per country and industry is unknown (in this case a homogenous distribution must be assumed (Carbon4 Finance, 2017)). Furthermore, revenue is a questionable proxy for physical activity (i.e., physical assets in a country): the revenue a company generates in country X is not necessarily correlated with its physical assets.

Recommendation: Only suggested as a backup option due to severe limitations. First, the country is the most granular spatial unit of this data source, making it challenging to incorporate the local aspects of biodiversity into the analysis.[15] Second, to determine the precise revenue distribution across industries and countries, it must be assumed that revenues are distributed homogeneously. Third, revenue is a questionable proxy for physical assets in a country. However, due to low implementation costs, this approach may suffice as a first screening to determine risks at sectoral level (without considering the importance and state of biodiversity integrity).

12 Refinitiv provides disaggregated revenue data using the Standard Industry Classification. Bloomberg makes use of its own BICS taxonomy. ***FactSet Hiearchy*** uses its own Hierarchy classification, covering 7,000 industry sectors and product groups when fully expanded.

13 The ***GLOBIO4 model*** generates geospatial data sets with scenario results for land use and mean species abundance (MSA) for plants, warm-blooded vertebrates (birds and mammals) and an overall MSA.

14 The WWF WRF includes land area-weighted averages for each indicator, risk category and risk type at country level. Risk scores are computed as the area-weighted average values based on the global data set, using the average industry weighting. Ranking is a simple rank, where 1 represents the country or territory of least risk. While these are not part of the risk assessment, they can be used for to compare countries and territories regarding their risks and respective rankings to use in a first screening and scoping of sites. This functionality will be included soon in the WWF BRF as well.

15 This is only feasible by assessing the land area-weighted average of an indicator at country level (for example, the average of Ecosystem Intactness in country X).

GUIDANCE B: COLLECTING LOCATION-SPECIFIC PROXY DATA ON SUPPLY CHAINS

In addition to the collection of location-specific data on portfolio companies' operational sites (Guidance A), it is important to also collect data on portfolio companies' supply chain sites. Guidance B explains in more detail which data sources and tools can be used by companies and financial institutions to approximate the biodiversity-related risks within supply chains.

Assessing biodiversity-related risks throughout the supply chain is not very different to assessing first-order risks conceptually nor in terms of required input data. The additional layer of information required is the importance of the supplier-customer relationship. The formula below illustrates that relationship: the biodiversity-related supply chain risk score per risk type, ***r***, of a Firm ***A*** is the sum of the first-order risk score per risk type (physical or reputational) of all ***n*** suppliers, weighted by a weighting factor, ***w***, per supplier, ***i***, which denotes the importance of the supplier-customer relationship:

$$\textit{Supply chain risk score}_{A,r} = \sum_{i=1}^{n} w_i \times \textit{1st order risk score}_{r,i}$$

Two approaches were identified and investigated as potential proxies for location-specific supply chain information.

1. Company-specific supply chain data (Approach I): This approach is similar to the data collection process for direct operational sites. The only additional data point required is the weight of the supplier-customer relationship. The approach looks as follows:

1. A list of suppliers per company is collected and a weighting per supplier-customer relationship is derived (ideally through company reporting or otherwise via third-parity data providers); and

2. The required data points as described in Guidance A are collected per supplier (location of sites, industry classification, business importance).

Approach I is conceptually simple but suffers from poor data availability: it is difficult to obtain a comprehensive list of suppliers per company of interest (Climate & Company, 2021)[16]. Yet companies have an inherent interest to gather the most relevant supplier data in order to manage their supply chain risks. Therefore, data collection through direct engagement with the supplier should be the first choice for real economy companies. An example would be a clothing retailer finding out and documenting the locations of their textile manufacturing sites, and then proceeding down the supply chain to find the location of their manufacturer's dye and textile providers and the locations of production of textile raw materials (e.g., cotton).

2. Input-output models (Approach II): This approach makes use of existing IO models and looks as follows:

1. The location-specific data of each company (location of sites, industry classification per site, business importance) are aggregated to the country-sector level to make it compatible with IO models;

2. The chosen IO model is applied to identify the upstream industries (and countries) associated with the country-sector split (obtained under Step 1); and

3. The importance and local integrity of biodiversity aspects is assessed for the upstream industry-country pairs.

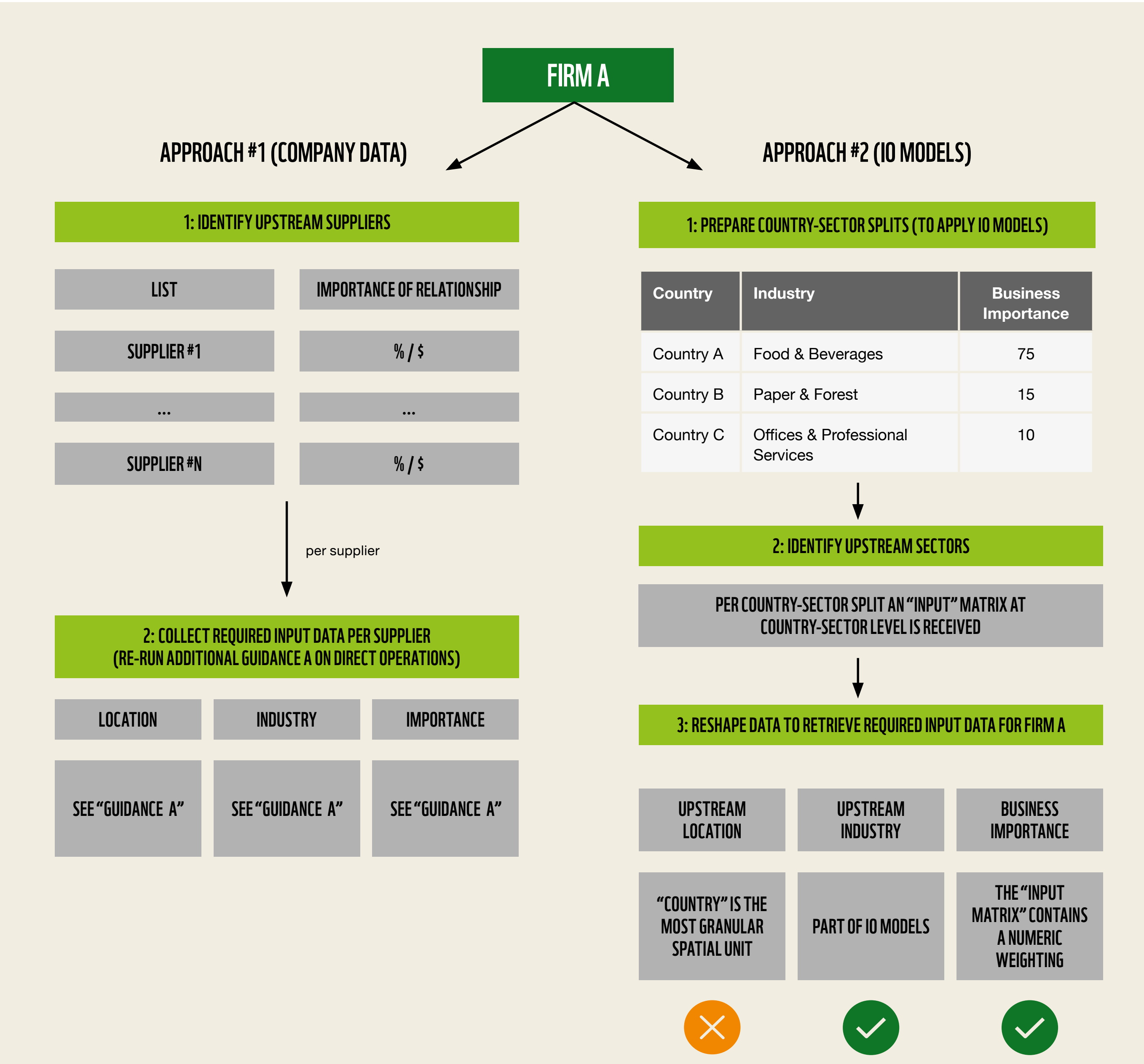
16 Looking at a sample of 1156 publicly listed companies headquartered in the EU, we found that 85% of the sample only disclosed less than 10 suppliers (based on FactSet Supply Chain Data). Reasons could be a low number of suppliers, an incomplete data extraction by FactSet, a low level of disclosure, or a combination of different factors. Given that the sample consists of listed firms in the EU, we conclude that retrieving comprehensive firm-specific supply chain data from data providers is still difficult (Erdmann, Hessenius, & Yahsi, 2022).

If a company or financial institution does not have access to supply chain data, they could use IO model outputs as a proxy. Take for example a car manufacturer in Germany. A financial institution conducting an analysis might not know where the manufacturer sources their steel and additionally where the ore used for that steel comes from. IO tables can tell the user that X% of German steel imports come from China and Y% of Chinese iron ore imports come from Australia. This gives a locational proxy for the whereabouts of the German car manufacturer's supply chain.

However, incorporating the importance and local integrity of biodiversity (Step 2) requires precise locations (coordinates), which is not given as IO models operate spatially at the country-level. Even though there are potential workarounds,[17] we currently suggest using them with extreme caution, since the workarounds come with high uncertainties and have not been tested thoroughly. Nonetheless, the second sub-step can already be leveraged to derive biodiversity-related upstream exposure scores for each company of interest (see Box 5).

Figure 10 visualises and compares the two approaches and their respective steps.

Figure 10: Comparison and complementarities of Approach I and Approach II in the collection of proxy supply chain data



17 One could, for example, extract a randomly chosen coordinate (or the centre) within a country and assess the importance and local integrity of biodiversity indicators based on this coordinate. However, this introduces a severe bias to the analysis. Another option is to assess the average importance and integrity of an indicator at the country level (for example the average integrity of surface water in country X). This might be accurate for smaller countries (such as Luxembourg) but could be completely misleading for larger countries (such as Russia).

While **Approach I, using firm-specific supply chain data**, is the most accurate, financial institutions and companies are not (yet) able to easily gather information at scale, as firm-specific supply chain data is patchy and largely incomplete (Climate & Company, 2021). Therefore, building on existing work (Banque de France, 2021), **Approach II, using IO models**, offers a second complementary, less accurate, but more practical alternative, based on sector- and country-level averages. IO models are generally derived from supply and use statistics from national account databases and help to show supply chains between industries and countries.

The following subchapters introduce the two approaches identified in more detail and discuss their coverage, advantages and disadvantages as well as available data points to approximate the required WWF BRF input data. The subchapters also contain workarounds to address typical data challenges, such as missing values. It ends with an overview of the comparison and recommendations regarding the available approaches.

1. COMPANY-SPECIFIC SUPPLY CHAIN DATA (APPROACH I)

Table 3 below describes the required data structure to assess the supply chain-related risks faced by the company of interest.

Table 3: Collecting data on a portfolio company's supply chain sites

	1: Identify suppliers		**2: Collect required input data per supplier (see Guidance A)**		
Company name	**Supplier**	**Importance of that relationship**	**Location of company sites**	**Industry classification**	**Business Importance**
Company A	Supplier 1	0.5	Lat/long	Industry A	%
	Supplier 1		Lat/long	Industry A	%
	Supplier 1		Lat/long	Industry A	%
	Supplier 2	0.5	Lat/long	Industry B	%
	Supplier 2		Lat/long	Industry B	%
	Supplier 2		Lat/long	Industry B	%
Relevance	Required to derive supply chain risks for Firm A		Required as input data to the WWF BRF tool		

1. Identifying a company's suppliers, including a weighting score per supplier-customer relationship

Identifying the list of suppliers

Ideally, the user receives a list of supply chain relationships for the company of interest (Firm A) along with a quantification of their (financial) importance. Different third-party data providers, such as FactSet,[18] Bloomberg,[19] or Refinitiv,[20] provide supplier-customer relationship data in a structured format. Data is collected by leveraging information based on the target company disclosing its suppliers.[21] One way to make the data set more complete is to add relationships based on reverse disclosures.[22]

18 Data product: *FactSet Revere Supply Chain Relationships*. FactSet data has been used for testing purpose. Therefore, data quality (coverage and accuracy) might differ subject to the chosen provider.

19 Data product: *Bloomberg Global Supply Chain Data.*

20 Refinitiv provides more information *here.*

21 For example, Nestle decided to disclose a list of its suppliers, covering 95 per cent of the *company's annual sourcing of raw materials.*

22 While Nestlé might only specify a limited number of suppliers, many more (often smaller) companies will disclose Nestlé as their customer. However, there is no guarantee that the list of supplier relationships is complete and, in many cases, is likely far from it.

Identifying the importance of each supplier

A logical measure of the financial importance of the customer-supplier relationship is the revenue dependency of the company on each of its suppliers as a fraction of the total revenue of that company. There are three potential ways to integrate this measure, in decreasing order of accuracy[23]:

- **Solution 1 – Disclosed data:** Third-party providers collect financial figures of supplier-customer relationships as part of their supply chain data products (example: Firm A is a customer of Firm B, generating X% of Firm B's revenue). However, this data is rarely disclosed: for a sample of 1461 listed companies headquartered in the EU, we only retrieved (incomplete) financial figures for 13% of the sample[24].
- **Solution 2 – Estimates:** In the absence of disclosed data, the user could derive estimated weights by determining the relative importance of the supplier-customer relationships[25]. FactSet, for example, provides an ordinal relevance ranking to fill the gaps mentioned in Solution 1. Based on FactSet Supply Chain Relationships data, a proprietary algorithm scores each relationship based on some hand-picked features (i.e., mutual disclosure, industry type, geography, etc). Users could also attempt to rank such relationships themselves. They would then have to transform this ranking into a normalised list of weights by making an assumption on how financial importance behaves as a function of the firm's place in the ordered list of suppliers. An example with four suppliers (S1, S2, S3 and S4) and an assumed linear relationship (starting with a minimal financial importance of 0.1), would be to assign the weights 0.4, 0.3, 0.2 and 0.1.
- **Solution 3 – Equal weighting:** The user equally weights all identified suppliers of a specific company.

2. Collecting location-specific proxy data on a supplier's operational sites (see Guidance A)

Feeding the data on the portfolio companies' supply chain sites into the WWF BRF (or WRF) Assess Module, requires location-specific data on the portfolio companies' suppliers. This proxy data can be generated in a similar manner to that used for a company's operational site. This is further explained in Guidance A.

2. INPUT-OUTPUT MODELS (APPROACH II)

In the absence of comprehensive, firm-specific supply chain data, a well-established way to gain insights into the supply chain links between different industries of the economy is to use IO models (see Figure 11). This has already been applied by some actors in this field, including Banque de France and the World Economic Forum (WEF)[26] and could be used as a bridging solution (until supply chain data is collected or becomes available).

Input-output tables are generally derived from supply and use statistics from national account databases, and thereby rely on sectoral averages at state level rather than relying on more granular firm-specific data. In more recent state-of-the-art IO models, international databases as well as trade statistics are also incorporated.

23 These methods also to apply to other potential metrics such as % of cost of goods or amount paid for purchased goods.

24 To get an idea on the order of magnitude, we assessed a sample of 1461 listed companies headquartered in the EU. For 87% of the sample (1261 companies) we retrieved no financial figures on supplier-customer relationships at all. For the remaining 13% at least some financial figures were stated by the source companies (Source: based on data from FactSet's Supply Chain Relationship database in 2022; reverse disclosures were not considered).

25 Example: a steel company is likely to be a more important supplier for an automotive company than, say, a supplier producing office materials.

26 While an extensive overview is beyond the scope of this chapter, it is informative to look at some relevant existing approaches. Firstly, the WEF and PwC Report Nature Risk Rising (WEF, 2020) compares direct and indirect dependencies across industry sectors using a preliminary version of ENCORE's dependency ratings. The authors used a global Multi-Region Input Output (MRIO) model to identify the sectors in the supply chain which were then weighted according to high, medium and low dependency. Secondly, the paper by Svartzman et al (2021): A 'Silent Spring' for the Financial System? (Banque de France, 2021) explores biodiversity-related financial risks for the French financial system (including transition risks as well as direct and indirect/upstream dependencies) using a sectoral approach which, in turn, was inspired by the pioneering study by van Toor et al. (2020). The study finds that 42 per cent of the value of securities held by French institutions are highly or very highly dependent on at least one ecosystem service. Finally, the Science Based Targets Network's business guide also contains an upstream/downstream dependency/impact rating, which builds on linking ENCORE with a specific MRIO called EXIOBASE (SBTN, 2020b).

Figure 11: Schematic depiction of the IO model approach

The resulting multi-regional tables describe the sectoral dependencies between countries (or sets of countries, depending on the spatial granularity). In other words, the supply relationships among the different industries can be shown (Value Balancing Alliance, 2021). Of particular importance is the table containing the input-output coefficients (known as the A matrix). The input coefficients, a_{ij}, can be interpreted as the share of costs in monetary terms for intermediate inputs of industry, i, to create one unit (e.g., one dollar) of industry, j. There are various multi-region input-output models (MRIOs) that could be used. For an overview, see Table 15 in the Appendix.

Limitations

- **Inherent assumptions of IO models:** The estimated relationships of IO models between the (sector, region) pairs are obviously not perfect, and depend on assumptions inherent to IO models. A discussion of inherent IO model limitations is beyond the scope of this paper, but we refer the interested reader to any standard text on the issue.[27]
- **Based on averages:** IO models are based on averages at the country and industry level. This means that, assuming the IO accurately represents on average the share of costs in monetary units of an intermediary industry on some other industry (e.g., of German car manufacturing on Polish steel production), it could still provide a very bad estimate for any specific company, especially if that company does things in a way that is out of the ordinary. So, the second obvious limitation is that the specific supply chains for each company are not taken into account and are instead assumed to be equal to the average way that supply chain is structured in the wider economy. Furthermore, using country aggregates does not allow investors to identify and address specific high-risk locations a company might have in its supply chain.
- **Static snapshot:** The IO models are a static snapshot in time, as the inter-industry linkages are derived for a certain year. The 10th version of the IO database derived from the Global Trade Analysis Project, for example, would illustrate the inter-industry and inter-country relationships for 2004, 2007, 2011 and 2014 (Aguiar, Chepeliev, Corong, McDougall, & van der Mensbrugghe, 2019).
- **Mapping of different classifications:** mappings between the industry and region classifications of the initial (sector, region) pairs for each company are not always perfect. The severity of the mismatch depends on the exact standard or method used to determine the former, as well as the IO model chosen. For instance, mapping the NACE industry standard (which comprises 615 industries at the most granular level) to the industries specified by the IO model EXIOBASE3 (with 163 industries, see Table 15) will result in a loss of information due to the lower granularity of the latter. Also, the problem of 'one-to-many' mappings can occur (e.g., if one NACE industry sector can be assigned to two or more industry sectors specified by EXIOBASE3) which requires further assumptions.

1: Prep work – Derive a list of sector-region pairs for each company

IO models work on a country-sector logic: for every monetary unit generated in, say, Germany (country) and car manufacturing (sector/industry), the IO models provide an extensive matrix from which countries and industries the monetary input is derived (say, 5 per cent from Polish steel manufacturing etc.). Therefore, for each company that is being assessed, the importance of each sector-country split is needed to map the company activities to an IO model. This is obtained by building on the proxy data collection in Guidance A (which includes a list of location-industry-importance triplets per company).

Figure 12: Illustrating prep work step

Company Name	Location of company site (Step 1)	Industry classification of site (Step 1)	Business importance of site % (Step 1)
Company A	Lat, Long (Country A)	Food and beverage production	25
	Lat, Long (Country A)		20
	Lat, Long (Country A)		15
	Lat, Long (Country A)		10
	Lat, Long (Country A)		5
	Lat, Long (Country B)	Paper & Forest Product Production	5
	Lat, Long (Country B)		5
	Lat, Long (Country B)		5
	Lat, Long (Country C)	Offices & Professional services	5
	Lat, Long (Country C)		5

Company Name	Country	Industry	Business importance per country-industry split
Company A	Country A	Food and beverage production	75
	Country B	Paper & Forest Product Production	15
	Country C	Offices & Professional services	10

MAPPING TO COUNTRY AND INDUSTRY CLASSIFICATION OF IO MODEL REQUIRED

27 One particularly good introductory text is Miernyk (1965).

In practice, the data collection from Guidance A needs to be transformed from ‘location-industry splits’ into ‘country-industry splits’ (see Figure 12), which need to be mapped to the corresponding country and industry classification of the selected IO model. An alternative solution that also works at scale (due to broad coverage) would be to define country-sector splits using the data source on disaggregated revenue splits (see Guidance A - 5): extracting disaggregated revenue splits at country and industry level from commercial data providers and applying the homogeneity assumption yields a comprehensive list of country-sector splits per company of interest. This has been used by Svartzman et al. (2021) and Lepousez et al. (2017).

2: Identify the upstream supply chain at the country and industry level by applying IO models

As mentioned above, the A coefficient matrix provides the quantitative basis for determining the relationships between different industries and regions. For each country-industry split, the IO model yields an A matrix of size ($N_{industries}$ x $N_{regions}$) where $N_{industries}$ is the number of industries distinguished by the IO model, and $N_{regions}$ the number of regions. The input coefficients, a_{ij}, can be interpreted as the share of costs in monetary terms for intermediate inputs of industry, i, to create one unit (e.g., US$ 1) of industry, j.

Therefore, the IO model (almost) yields the required data points per supplier:

- The **location of company “sites”** is identified at the country-level (instead of the precise longitude/latitude information);
- The **industry classification** is derived from the IO model’s industry classification; and
- The **business importance** of each location-industry pair is identified through the input coefficients, a_{ij}, (instead of the importance per location-industry pair of own sites, it is the importance of the upstream industry-country pair).

This information can be leveraged to generate a helpful interim result about the supply chain-related risks per company of interest (see Box 5). To continue, the user needs to prepare the required data structure for Step 2, which requires precise coordinates. This is currently problematic and requires complex workarounds, discussed in the next paragraph.

3: Preparing data input (to include the location-specific dimension)

The fundamental difference to Approach 1 (firm-specific supply chain data) is that precise longitude and latitude information cannot be provided since the most granular spatial unit of IO models is at country-level. A potential workaround could be to assess the land area-weighted average of an indicator at country level (for example, the average of Ecosystem Intactness in country X). This clearly would work better with smaller countries and could be extremely misleading for countries with larger territories and/or high land use heterogeneity. Therefore, it is very important that the world’s largest (at least Russia, Canada, United Stated, China, Brazil, Australia, India, Argentina, Kazakhstan and Algeria) are sub-divided into sub-national divisions (admin level 1) to avoid results being averaged across the climatic and land use variability to one value. The WWF WRF includes land area-weighted averages for each indicator, risk category and risk type at country level. Risk scores are computed as the area-weighted average values based on the global data set, using the average industry weighting. Ranking is a simple rank, where 1 represents the country or territory of least risk. While these are not part of the risk assessment, they can be used for to compare countries and territories regarding their risks and respective rankings to use in a first screening and scoping of sites. This functionality will be included soon in the WWF BRF as well.

To the best of our knowledge, using IO models to assess supply chain risks has not been combined with country-level importance and integrity values of biodiversity. This is time consuming and builds on the questionable assumption that country level importance and integrity values are an accurate proxy for location-specific importance and integrity values. However, there is work in progress to make IO models more spatially granular.[28]

28 See, for example: Croft, S. A., West, C. D., & Green, J. M. (2018).

BOX 5 :
DERIVING UPSTREAM EXPOSURE SCORES PER COMPANY WITHOUT INCORPORATING THE LOCATION-SPECIFIC DIMENSION

The output of IO models can be used to compute the upstream exposure score per sector-country split (and ultimately per company). After splitting corporate location-level data into sector-region pairs and applying an IO model, the user produces a country-sector input matrix per country-sector split.

Company Name	Country	Industry	Business importance
Company A	Country A	Food and beverage production	75
	Country B	Paper & Forest Product Production	15
	Country C	Offices & Professional services	10

(IO model)

	Sector 1	...	Sector N
Country 1			
...			
Country N			
Sum per sector	∑	∑	∑

Concordance table to WWF BRF sector classification

Sum per sector	∑	∑	∑

Multiplied by BRF industry weighting per risk indicator

	Sector 1	...	Sector N
Risk Indicator1	(0-5)	(0-5)	(0-5)
...	(0-5)	(0-5)	(0-5)
Risk Indicator N	(0-5)	(0-5)	(0-5)

After mapping the industry classification of the IO model to the WWF Risk Filter industry classification, the user can calculate the importance of each BRF upstream industry to the main company, which can be interpreted as the weight per industry, ***s***, w_s (i.e., the value of industry s's production, integrated into the value produced by the main industry). To retrieve the overall exposure score per upstream industry sector, the user derives the direct exposure score DE_s, per upstream industry, ***s***, by taking the mean across all ***n*** industry materiality ratings per risk indicator, ***RI***, resulting in a value between 0 and 5 (the scale of the BRF industry materiality ratings).

$$DE_s = \sum_{i=1}^{N} \frac{RI_i}{n}$$

Interim result (example): One upstream industry of company A's country-sector split "Country A – Food and beverage" is Upstream Industry 1. For Upstream Industry 1, the generic industry materiality ratings are known. The average of all industry materiality ratings for Sector 1 makes the exposure comparable across biodiversity indicators and ecosystem services.

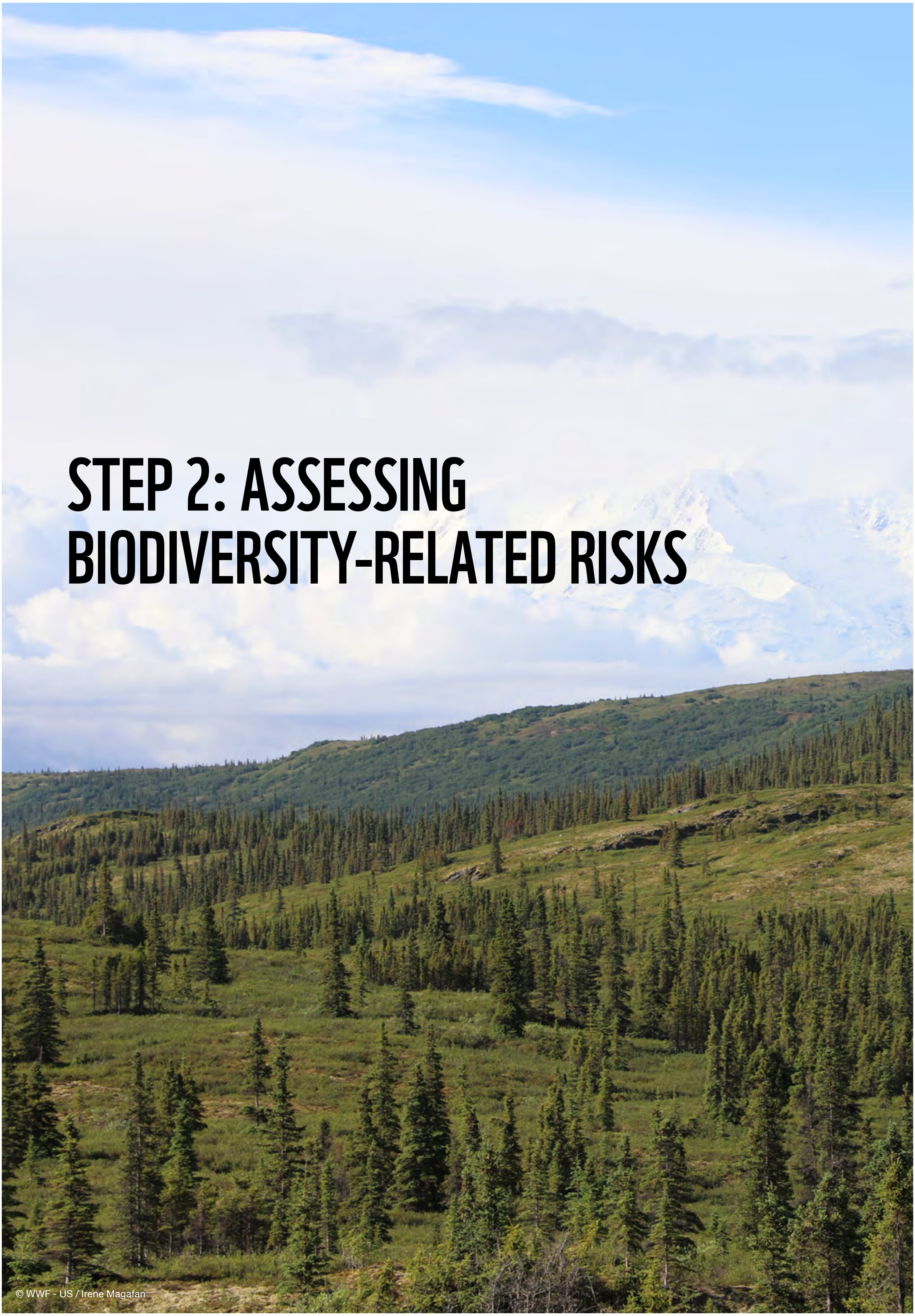
To retrieve the aggregated, upstream supply chain exposure score per country-sector split, ***UE***, (for example country A, Food and beverage), one weights, DE_s,by its weight, w_s.

$$UE = \sum_{S=1}^{N} w_s \times DE_s$$

This yields an upstream score per country-sector split, which can be aggregated to the company-level using the weight of each country-sector split (yielding a score between 1 and 5, where 5 stands for high potential exposure to biodiversity-related risks in the upstream supply chain). The results could also be disentangled and presented by risk indicator.

Sources: Adapted from Banque de France (Banque de France, 2021), partly building on the BIA-GBS methodology (Biodiversity Impact Analytics powered by the Global Biodiversity Score; developed by *Carbone4 and CDC*

STEP 2: ASSESSING BIODIVERSITY-RELATED RISKS



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After scoping the assessment (Step 0) and collecting location-specific company and supply chain data (Step 1), the required input data is fed into the WWF BRF (or WRF) Assess Module which calculates biodiversity-related (or water-related) physical and reputational risk scores for each provided site.

Biodiversity-related risks arise from companies' dependencies and impacts, in combination with the importance and local and global state of biodiversity integrity. Subsequently, the WWF BRF Assess Module combines the sites' industry materiality rating (0A) and the biodiversity importance or integrity rating based on sites' geographic location (0B) into a scape risk score for each of the 33 different biodiversity importance and integrity indicators (see 'Scape risk calculation' below for more detail).

To capture the complexity of the topic, a comprehensive structure is needed to organise and structure the biodiversity indicators to ease interpretation and translate the assessment to business relevant terms. The WWF BRF employs a risk hierarchy to group indicators in thematically relevant risk categories and risk types that align with major frameworks, such as TNFD or SBTN (see 'Grouping indicators using biodiversity risk hierarchy' below for more detail).

Step 2A: Calculating scape risk

Scape risk is a risk score, on a scale of 0 to 5, assessing a specific aspect of biodiversity at a specific site for a specific industry (see Table 4). It is determined by two factors: (a) industry materiality (e.g., paper mills are very highly dependent (5) on timber availability); and (b) the local state of biodiversity aspects (e.g., indicator 'Limited Timber Availability' is rated as being at very high (5) if there is no timber available). For each site, all 33 indicators of physical and reputational risk are calculated by the WWF BRF tool.

Mathematically, this can be done by taking the arithmetic mean of the industry materiality (impact/dependency) rating, ***IM***, for indicator, ***i***, and industry sector, ***s***, and the indicator assessment, ***IA***, for indicator, ***i***, at site (location), ***l***:

$$\textit{Scape risk}_{i,s} = \frac{IM_{i,s} + IA_{i,l}}{2}$$

Combining both via the arithmetic mean captures two assumptions: 1) the higher the industry materiality rating, the higher the potential risk exposure, and 2) the higher an indicator's risk score, the higher the potential threat. This means that the scape risk for each indicator ('Limited Timber Availability' in the example below) will vary depending on the location and the industry classification of a company location, as illustrated in Table 4.

Table 4: Scape risk calculation – example

Location of company site	Integrity rating for Limited Timber Availability	Industry	Industry-specific weightings of Limited Timber Availability	Scape risk
Nashville, TN, USA	1 - Very low risk	Offices and professional services	1 - Very low dependency	1
Nashville, TN, USA	1 - Very low risk	Paper and forest product production	5 - Very high dependency	3
Reggane, Algeria	5 - Very high risk	Offices and professional services	Not applicable for this industry	0
Reggane, Algeria	5 - Very high risk	Paper and forest product production	5 – Very high dependency	5

Step 2B: Calculating site-level risk

In a biodiversity risk analysis, a large number of biodiversity indicators are required to capture the system's complexity. However, using many indicators poses problems for aggregating risk over a single company site, as outliers and indicators of minor business importance can influence the final aggregation and lead to under- or overstatement of risk. It is therefore important to employ a risk hierarchy that groups indicators in in thematically relevant risk categories and risk types and an aggregation scheme that will highlight aspects of biodiversity risk that are business important without being diluted by outliers or indicators of minor business importance.

The current WWF BRF tool employs a risk hierarchy that groups indicators (LEVEL 3) in thematically relevant risk categories (LEVEL 2), and only then to risk type (LEVEL 1) (see Figure 4). This has a number of advantages. First, when using a large number of different indicators to assess biodiversity risk, the influence of each single indicator is reduced. That means that if all indicators were aggregated into one single number, a few high-risk indicators could be averaged out with a large number of low-risk indicators. Grouping the indicators into thematically relevant categories reduces this averaging risk, because even one high-risk indicator within a risk category will influence and therefore be visible in the risk category score. Secondly, thematically relevant risk scores and risk types can give users a better overview of why a site might experience high risk, without having to understand the risk assessment at the indicator level. Third, such grouping is aligned with other reporting standards (e.g., TNFD), which do not require reporting at the indicator level, but only, for example, for physical risk.

The 75th percentile method is used both in the aggregation of indicators to risk categories and from risk categories to risk types. Percentiles as a measure takes the value of the n^{th} percentage number in the distribution.[29]

Using the 75th percentile emphasises high-risk scores. As shown in Table 5, this method emphasises the right tail of risk distributions (higher risks). Although the mean (average) of indicators for Company A is lower than that of Company B (a mean of 2.2 compared to a mean of 3), the high scape risk of Indicator 4 and Indicator 5 are emphasised. This method helps to inform companies that certain sites might be highly exposed to biodiversity-related risks that could be integral to business operations. This is important, because even a single high-risk issue could result in considerable damage to a business or its supply chain. The omission of a high-risk score should therefore be avoided. For example, a water utilities site might be below average risk for most indicators, such as soil condition and invasive species, but their core business relies on indicators such as water availability and water condition. Though the calculation of scape risk takes this importance into account, these extremely relevant risks would be lost in mean aggregation. Using the 75th percentile method helps to emphasise the important exposures, such as water availability and water condition in the case of a water utility site location.

Once the risk assessment has been conducted, a company can identify the areas of operations and geographical areas in which it has the highest risk. Those operational and geographic areas should then be subject to 'deep dives' to understand the specific local context better and identify response actions to reduce those risks (e.g., by conserving and/or restoring biodiversity in those specific geographies).

Table 5: Illustrating aggregation method "Percentile"

	Aggregated scape risk per indicator in risk category					75th Percentile	Mean
	Indicator 1	Indicator 2	Indicator 3	Indicator 4	Indicator 5		
Company A	1	1	1	4	5	4.5	2.2
Company B	3	4	2	3	3	3.5	3

29 For example, the 75th percentile of a distribution with eight observations would be the value of the sixth observation.

STEP 3: AGGREGATING RISKS TO THE COMPANY AND PORTFOLIO LEVEL (GUIDANCE C)

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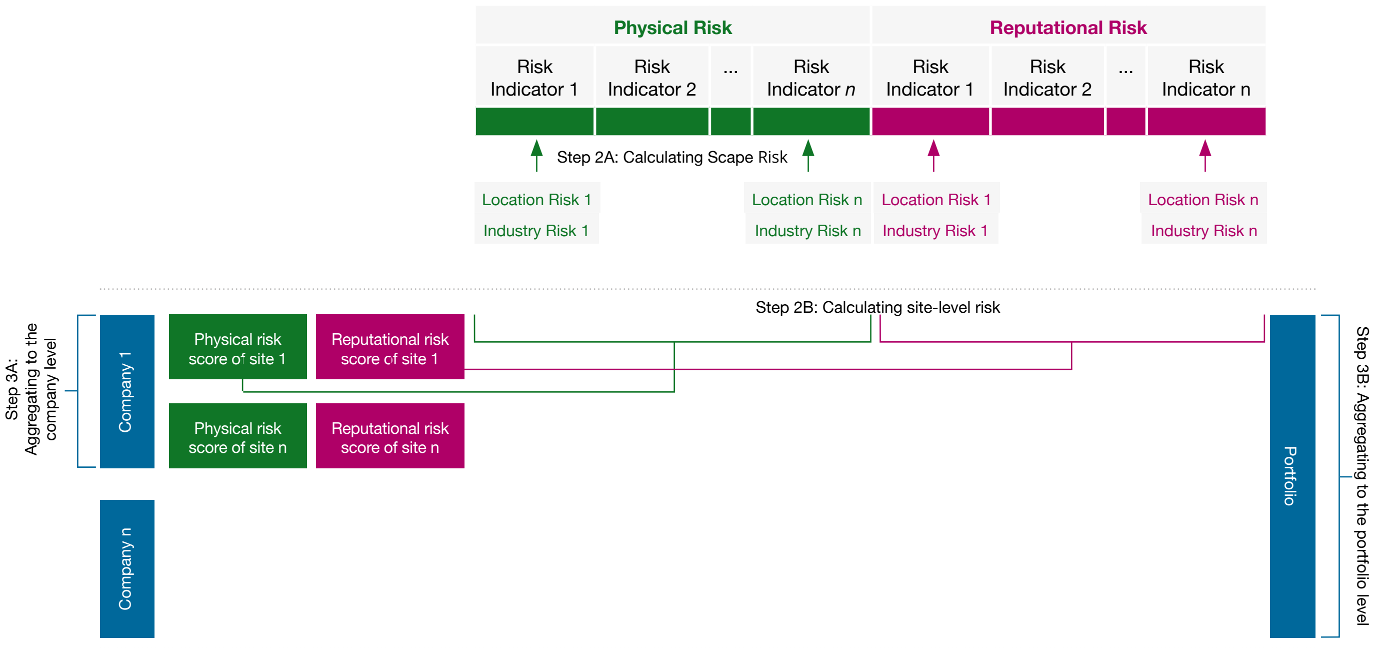
It is important to note that not only does the WWF BRF Assess Module provide a scape-level assessment, it also offers overview assessments per company or group.[30] It does not, however, create an aggregate risk score per company, group or portfolio. Instead, it shows the number of sites that fall within the five risk-score classes. WWF and Climate & Company, therefore, developed further guidance on aggregating the results to the company and portfolio level.

This section explains in more detail how the output data from the WWF BRF Assess Module can be aggregated to serve different use cases and user groups. It predominantly targets financial institutions, as the aggregation is particularly relevant to compare portfolios and portfolio companies at scale. Physical and reputational risk scores are aggregated separately, as they form distinct categories of risk: Physical risk is pertinent to the supply-side dimension of a company's production while reputational risk is found more on the demand side.[31] The suggested aggregation steps are outlined in Figure 13.

Figure 13: Illustrating aggregation steps



STEP 3A: AGGREGATING TO THE COMPANY LEVEL (ACROSS COMPANY SITES)

Step 2A and 2B yield a risk aggregate score for each company site, per LEVEL 2 'risk categories' and Level 1 'risk types'.

Every location-specific risk contributes to a company's total potential biodiversity-related risk. One can measure the business importance of a site as a percentage. This can be done following Guidance A: Collecting location-specific proxy data on portfolio companies' operational sites. A final company risk score can then be computed by weighing each site's grouped scape risk by its business importance. The sum of a company's business importance should equal 1. The calculation is shown in the formula below.

An aggregated company risk indicator, ***RI***, per company, ***c***, and per LEVEL 1 risk type, ***r***, can be computed by multiplying the business importance, ***BI***, per site, ***i***, with the aggregated/grouped site risk of site, ***i***, per risk type, ***r***.

$$RI_{c,r} = \sum_{i}^{n} Site\ Risk_{i,r} \times BI_{i},$$

with ***N***= total number of sites per company

30 The WWF BRF allows users to assign sites to groups to analyse a subset of sites. The groups can be freely defined by the user. Examples include: groupings by supply chain management (classes; groupings by geography; groupings by commodity.

31 Physical risks might increase production costs or disrupt the production process (supply side). Reputational risks are rather demand-driven as consumers or investors might stop purchasing goods or stop investing in the company.

As companies can operate globally, each one of their sites could be exposed to considerably different biodiversity-related risks. Additionally, each site has a different importance to the functioning of the company's operations. By aggregating each site risk score weighted by its business importance, one can determine a company's overall physical and reputational risk score. For example, a telecommunications company has three sites spread across two different countries. Each site has a distinct physical (and reputational) biodiversity risk score based on its location and industry-related dependency or impact, for example, a physical risk score of 5, 4 and 1, respectively. Each site also has a distinct business importance, for instance, because a certain site is where an important radio tower node or headquarter is located. The business importance is quantified per site as a percentage that together over all sites sums up to 1, for example, 0.6, 0.2, 0.2. By multiplying and adding the business importance and the site-specific risk scores, an overall physical risk score for the company can be determined: a physical risk score of 4 (i.e., 5x0.6 + 4x0.2 + 1x0.2 = 4)

STEP 3B: AGGREGATING TO THE PORTFOLIO LEVEL (ACROSS COMPANIES)

Within a portfolio, the weight of an individual asset or company is derived from the percentage of its value compared with the total portfolio value. An aggregated risk score for a portfolio can be calculated by multiplying individual companies' risk scores by their portfolio weight (see below).

An aggregated portfolio risk score, ***P***, for each LEVEL 1 risk type, and portfolio, ***p***, can be computed by multiplying the portfolio weight of a company, $\boldsymbol{W_c}$, to the aggregated company risk score, ***RI***, for company, ***c***, and per risk type, ***r***.

$$P_{p,r} = \sum_{c}^{n} RI_{c,r} \times W_c$$

with ***N***= total number of companies in the portfolio

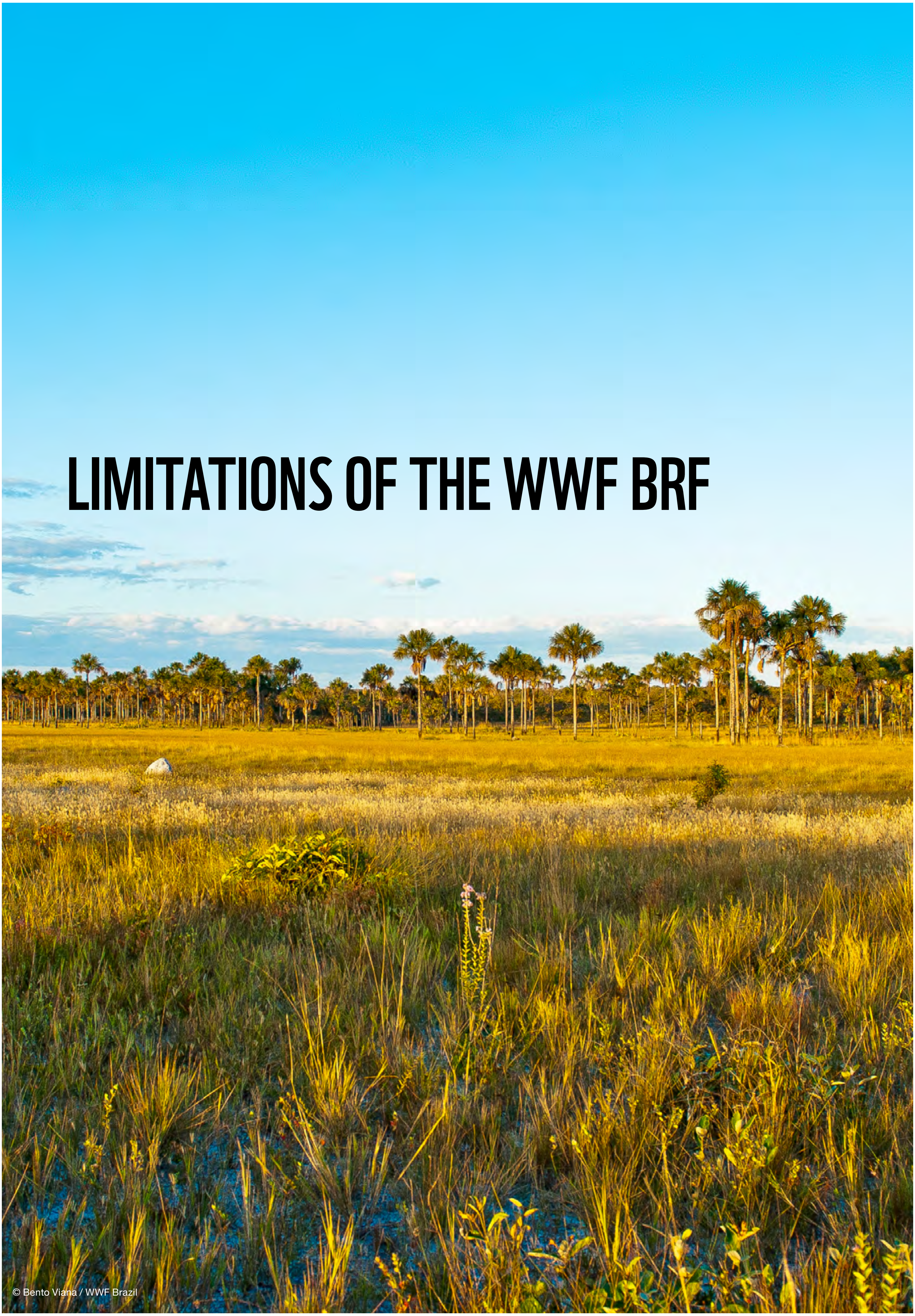
In practical terms this aggregation could also be applied to a portfolio of assets. Imagine a portfolio that consist of a mix of equities and bonds. Each equity and bond can be viewed as a company and is the financial realisation to an assortment of different site-specific locations. Using the aggregation methods described in the previous step allows us to find asset specific risks. Each one of these assets has a specific market value that all together form the portfolio's total value. To find the portfolio's total risk the sum is taken of each asset's risk is weighted by their value as a percentage of the portfolio's total value.

STEP 3C: AGGREGATING SUPPLY CHAIN RISKS

While the subchapters above have focused on deriving first-order risks at the site, company and portfolio level (i.e., risks stemming from portfolio companies' own operations), it is also possible to aggregate upstream supply chain risks across companies and portfolios (i.e., risks stemming from the portfolio companies' suppliers). With the additional data point on the supplier-customer relationships, the assessment of biodiversity-related risks throughout the supply chain is conceptually not different to assessing first-order risks. The additional layer of information is the importance of each supplier-customer relationship. The biodiversity-related supply chain risk score for risk type, ***r***, of a Firm ***A*** is the sum of the first-order risk score for each risk type (physical or reputational) of all ***n*** suppliers, weighted by a weighting factor, ***W***, for supplier, ***i***, which denotes the importance of the supplier-customer relationship:

$$\textit{Supply chain risk score}_{A,r} = \sum_{i=1}^{n} W_i \times \textit{1st order risk score}_{r,i}$$

LIMITATIONS OF THE WWF BRF



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This section describes the current cross-cutting limitations of the methodology and suggests avenues for future research.

Potential risk instead of actual risks

The WWF BRF assessment is currently, in a nutshell, based on the location of company sites, their industry classification and corresponding industry materiality rating, and the local state of biodiversity. For biodiversity-related risks to become material to a business depends on three factors: 1) the likelihood of threats emerging (i.e., the local state of various aspects of biodiversity), 2) the degree of a company's exposure to these threats (i.e., the industry materiality) and the vulnerability of the company to the threat (i.e., the company's preparedness and response) (WWF, 2022a). The current BRF assessment covers the first two factors, but not the last. Incorporating company preparedness and response is crucial to move from the potential to the actual risks that a company faces. The resulting physical and reputational risk scores should therefore be carefully interpreted as potential risks rather than actual risks. The planned inclusion of an operational assessment will better allow companies and financial institutions to fine-tune industry materiality ratings based on a detailed questionnaire.

Risk score rather than a monetary valuation of risks

Financial risk refers to the risk inherent to an investment, where there is a quantifiable amount of money that could be lost. The current assessment does not produce a financial risk metric (such as Value at Risk). This will require further work, in particular on damage functions that translate the local state of biodiversity into negative impacts on a company's business model.

Assessment of biodiversity-related opportunities not yet included

The WWF BRF currently provides an assessment of biodiversity-related physical and reputational risks. However, there are also biodiversity-related business opportunities that arise from conservation and restoring and mitigating existing damage. Future iterations of the WWF BRF will also include this opportunity perspective. Other planned developments of the tool include: the addition of other risk types (e.g., regulatory and market risk); the creation of a Respond Module, which will allow users to start tackling risks across sites through risk reduction and shifting towards a more nature-positive business model.

Limited data for supply chain assessment

The BRF Methodology Documentation provides guidance for companies and financial institutions on how to approximate biodiversity-related risks in supply chains. Two approaches were presented in the Guidance B: Approach I on company-specific supply chain data and Approach II on IO models. Both approaches have their own inherent limitations. The first approach suffers from the limited availability of company-specific supply chain data. The IO model approach is based on averages at the country and industry level (and might therefore be misleading for companies operating outside the norm); and the inter-industry relationships are a static snapshot.

Limitations inherent to our modelling principles

- **Applying this methodology at scale requires workarounds**. For financial institutions in particular, the WWF BRF Methodology documentation describes different proxies and data sources to circumvent data gaps (for example using third-party data on the corporate hierarchy instead of reported data). The workarounds make the application feasible but may offer a false sense of accuracy or completeness. The case study presented in Appendix Guidance A: Overview of data providers shows that different data inputs lead to different results.
- **Point-in-time assessment**. As of writing in January 2023, the assessment is a point-in-time evaluation and is only as up to date as the data set of the underlying biodiversity indicator itself (e.g., Ecosystem Intactness & Connectivity is based in part on 2016 data.). The data will be updated regularly to incorporate the most recent data sets. It should be noted that at this point in time the WWF BRF does not include information on how these risks will potentially evolve following different climate and socio-economic scenarios._
- **Point location as site input.** Currently, the WWF BRF tool only allows for point location input (address or longitude and latitude) to identify the location of a company's site. Incorporating a polygon (such as arable farming) or linear infrastructure (such as railway lines) is currently only possible by manual workarounds (e.g., by extracting the centroid of the polygon or by extracting multiple sites along a linear infrastructure).
- **Spatial granularity of assessment units differs.** Since biodiversity loss is a spatially explicit problem, it is important to consider the local variations of biodiversity in any assessment of corporate biodiversity-related risk. The global biodiversity data in the WWF BRF varies in scale between fine-scale raster data (30m x 30m) to country-level data. To impose a common scale, the raw data is aggregated or transposed to HydroSHED Level 7, as it represents a degree of functional coherence for measuring biodiversity. Some spatial granularity is lost through the aggregation.

- **Level of abstraction.** Each data set that is included in the WWF BRF has been translated to a risk score of 1-5. This reduces the complexity of the data to single numbers, which allows for comparison between the different indicators. This, however, also reduces the complexity of biological and ecological context and introduces artificial classifications to fit every global data set into. As the tool is meant to be a global prioritization tool, these abstract scores should only be used to give the user a first overview of biodiversity risk within the supply chain. When high risks have been detected, it will always be helpful to consult not only the source data, but also further leading resources and local data sets to investigate specific risk of a site.
- **Robustness of data.** To ensure the robustness of the data the utmost care has been taken to select only the most up-to-date, reputable, global and mostly freely available data sets to assess each indicator. However, due to data availability of global data sets, some proxy data had to be included. Furthermore, users are advised on how the data should be used and interpreted and the WWF BRF team offers support in data interpretation. The WWF BRF team will continuously work on improving the robustness through testing and consultation.
- **Error of omission.** The WWF BRF is based on 56 different data sets covering a wide variety of biodiversity risk aspects. This was done to avoid an approach in which the complex topic of biodiversity is reduced to only one or few indicators. The current set of indicators have been carefully selected to try to achieve a balance between completeness, usefulness for the user and data availability. However, there are more aspects to biodiversity risk that could be included in the tool. The explanations of the different indicators contain disclaimers if other data sets were considered but were not available or are planned to be included in future iterations of the tool. As new data becomes available and the inclusion of more data becomes necessary, indicators/data sets may be added or removed.
- **Gap in trade-offs**. Interrelations, trade-offs and feedback loops between different ecosystems and the services they provide are currently not considered. This is relevant due to the potential trade-offs that can occur between different services, where the provisioning of one service can decrease a different service.
- **Industry materiality and the importance and integrity of biodiversity as key drivers of results.** Results are sensitive to a) the industry materiality rating linked to companies' industry classification; and b) the thresholds of converging spatial biodiversity data into a score of 1 to 5. Both elements are key drivers of the results. At this point in time, the WWF BRF does not consider potential actions that have already been taken to reduce or mitigate biodiversity risk but is only a reflection of potential risk due to location and industry-associated activities.
- **Natural resources are sourced from surrounding areas.** For provisioning services, such as timber availability, it is assumed that natural resources are sourced directly from the surrounding area. This may or may not be the case.

While there are several limitations to the WWF BRF assessment, it nonetheless provides a helpful starting point for companies and financial institutions to understand and address biodiversity-related risks within their portfolios. The portfolio screening and prioritisation enables users to better understand, assess and respond to biodiversity-related risks. The WWF BRF also addresses certain gaps in the biodiversity risk assessment landscape such as spatially explicit assessment and the consideration of supply chain elements.[32] A few avenues of improvement are already planned, including:

- **Incorporating corporate response elements**, where users receive a list of suitable response actions for and across company sites (i.e., the Respond Module),
- **Additional risk types,** such as regulatory risk and market risk;
- **Additional refinement on sector granularity,** e.g. by incorporating an operational risk assessment;
- **Incorporating more local data sets** to allow assessment at a smaller scale
- **Incorporating the aggregation to the company and portfolio-level** to tailor the WWF BRF and WRF Assess Modules output more to the needs of financial institutions

32 For more information, please refer to the report 'Tackling Biodiversity Risk' (WWF, Climate & Company, 2023).

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APPENDIX STEP 0: SCOPING THE ASSESSMENT

APPENDIX 0.1: WWF RISK FILTER INDUSTRY SECTOR CLASSIFICATION

Table 6: WWF Risk Filter industry sectors

WWF Risk Filter Industry Sector	Associated Activity Guidelines
Agriculture (animal products)	Large-scale livestock (beef and dairy)
	Small-scale livestock (beef and dairy)
Agriculture (plant products)	Large-scale irrigated arable crops
	Large-scale rainfed arable crops
	Small-scale irrigated arable crops
	Small-scale rainfed arable crops
Appliances and general goods manufacturing	Manufacture of machinery, parts and equipment
	Houseware and specialities production
Automotive, electrical equipment and machinery production	Manufacture of machinery, parts and equipment
	Tyre and rubber production
Chemicals and other materials production	Catalytic cracking, fractional distillation and crystallization
	Incomplete combustion
	Polymerisation
	Vulcanisation
	Synthetic fertilizer production
	Cryogenic air separation
	Gas adsorption
	Membrane technology
	Natural gas combustion
	Recovery and separation of carbon dioxide
	Solids processing
Construction materials	Glass making
	Construction materials production
Electric energy production – combustion (biomass, coal, gas, nuclear, oil), geothermal energy	Infrastructure holdings
	Electric/nuclear power transmission and distribution
	Nuclear and thermal power stations
	Biomass energy production
	Geothermal energy production
Electric energy production – hydropower	Infrastructure holdings
	Hydropower production
	Electric/nuclear power transmission and distribution
Electric energy production – solar, wind	Infrastructure holdings
	Solar energy provision
	Wind energy provision
	Electric/nuclear power transmission and distribution
Electronics and semiconductor manufacturing	Electronics and hardware production
	Manufacture of semiconductor equipment
Fishing and aquaculture	Aquaculture
	Freshwater wild-caught fish
	Saltwater wild-caught fish
Food and beverage production	Alcoholic fermentation and distilling
	Processed food and drink production
Food retailing	Infrastructure holdings
General or speciality retailing	Infrastructure holdings
Health care, pharmaceuticals and biotechnology	Infrastructure holdings
	Life science, pharma and biotech manufacture
	Life science, pharma and biotech tools and services
	Provision of health care
	Managed health care

WWF Risk Filter Industry Sector	Associated Activity Guidelines
Hospitality services	Cruise line provision
	Hotels and resorts provision
	Restaurant provision
Land development and construction	Construction
	Infrastructure builds
Metals and mining	Alumina refining
	Mining
	Iron extraction
	Iron metal production
	Metal processing
	Steel production
Offices and professional services	Infrastructure maintenance contracts
	Infrastructure holdings
	Financial services
	Leisure facility provision
	Real estate activities
	Environmental and facilities services
Oil, gas and consumable fuels	Mining
	Oil and gas drilling
	Manufacture of machinery, parts and equipment
	Oil and gas services
	Oil and gas exploration surveys
	Oil and gas refining
	Oil and gas storage
	Oil and gas transportation
	Gas distribution
	Gas retail
Paper and forest product production	Large-scale forestry
	Production of forest and wood-based products
	Small-scale forestry
	Paper packaging production
	Production of paper products
Telecommunication services (including wireless)	Cable and satellite installations on land
	Fibre-optic cable installation (marine)
	Telecommunication and wireless services
Textiles, apparel and luxury good production	Jewellery production
	Natural fibre production
	Synthetic fibre production
	Footwear production
	Production of leisure or personal products
	Tobacco production
Transportation services	Infrastructure maintenance contracts
	Distribution
	Airport services
	Marine transportation
	Marine ports and services
	Railway transportation
	Construction
Water utilities and water service providers	Water services (e.g. waste water, treatment and distribution)

APPENDIX 0.2: INDUSTRY MATERIALITY MATRIX

Table 7: Industry materiality matrix (industry-specific weightings)

	BRF Indicators	Impact/ Dependency	Industry																									
			Agriculture (animal products)	Agriculture (plant products)	Appliances & General Goods Manufacturing	Automotive, Electrical Equipment & Machinery Production	Chemicals & Other Materials Production	Construction Materials	Electric Energy Production - Combustion (Biomass, Coal, Gas, Nuclear, Oil), Geothermal Energy	Electric Energy Production – Hydropower	Electric Energy Production - Solar, Wind	Electronics & Semiconductor Manufacturing	Fishing and aquaculture	Food & Beverage Production	Food Retailing	General or Speciality Retailing	Health Care, Pharmaceuticals and Biotechnology	Hospitality Services	Land Development & Construction	Metals & Mining	Offices & Professional Services	Oil, Gas & Consumable Fuels	Paper & Forest Product Production	Telecommunication services (including wireless)	Textiles, Apparel & Luxury Good Production	Transportation Services	Water utilities / Water Service Providers	Other (Average of all sectors)
Physical Risk																												
1.1	Water Scarcity	Dependency	5	5	4	4	4	5	5	5	3	4	5	5	2	2	4	4	3	5	2	4	5	2	5	4	5	4
1.2	Forest Productivity and Distance to Markets	Dependency	0	0	0	0	0	4	4	0	0	0	0	0	0	0	0	2	4	4	0	4	5	2	5	2	0	1
1.3	Limited Wild Flora & Fauna Availability	Dependency	1	1	0	3	1	1	0	0	0	0	3	3	0	0	3	2	2	0	0	0	3	0	2	0	0	1
1.4	Limited Marine Fish Availability	Dependency	0	0	0	0	0	0	0	0	0	0	5	0	0	0	0	2	0	0	0	0	0	0	0	0	0	1
2.1	Soil Condition	Dependency	4	5	0	0	0	0	0	0	0	0	1	0	0	0	0	1	1	0	0	0	5	0	0	0	1	1
2.2	Water Condition	Dependency	5	4	2	2	3	2	2	3	2	2	5	4	2	2	3	4	2	2	2	2	4	2	2	2	4	3
2.3	Air Condition	Dependency	3	3	2	2	2	2	2	1	2	2	3	2	1	1	1	3	3	3	3	3	3	0	2	2	2	2
2.4	Ecosystem Condition	Dependency	2	2	0	0	0	0	0	0	0	0	5	0	0	0	0	0	0	0	0	0	4	0	0	0	0	1
2.5	Pollination	Dependency	2	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	1
3.1	Landslides	Dependency	5	5	4	4	4	4	4	4	4	4	5	4	4	4	4	4	4	4	4	4	5	4	4	5	5	4
3.2	Wildfire Hazard	Dependency	4	4	3	3	3	3	3	3	3	3	4	3	3	3	3	3	3	3	3	3	5	3	3	4	4	3
3.3	Plant/Forest/Aquatic Pests and Diseases	Dependency	4	4	0	0	0	0	0	0	0	0	4	4	0	0	4	1	0	0	0	0	4	0	0	0	0	1
3.4	Herbicide Resistance	Dependency	4	4	0	0	0	0	0	0	0	0	3	0	0	0	0	1	1	0	0	0	4	0	0	0	2	1
3.5	Extreme Heat	Dependency	5	5	3	3	3	3	4	3	3	3	5	3	3	3	3	4	4	4	4	4	5	3	3	4	4	4
3.6	Tropical Cyclones	Dependency	5	5	4	4	4	4	4	4	4	4	5	4	4	4	4	4	4	4	4	4	5	4	4	5	5	4
4.1	Tourism Attractiveness	Dependency	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	1	0	0	0	0	0	0	0	0	1
5.1	Land, Freshwater and Sea Use Change	Impact	5	5	1	1	1	1	1	5	3	1	5	1	1	1	1	1	5	5	1	5	5	3	1	5	1	3
5.2	Tree Cover Loss	Impact	5	5	1	1	1	5	4	4	1	1	1	1	1	1	1	3	5	5	1	5	5	5	1	5	1	3
5.3	Invasives	Impact	3	3	0	0	0	2	0	2	0	0	3	2	2	2	0	3	2	2	0	2	3	2	0	3	3	2
5.4	Pollution	Impact	5	5	5	5	5	5	5	4	4	5	5	4	4	4	5	2	5	5	2	5	4	2	5	4	2	1
Reputational Risk																												
6.1	Protected/Conserved Areas	Impact	5	5	3	3	3	3	5	4	4	3	3	3	1	1	3	1	5	5	1	5	5	3	3	5	3	3
6.2	Key Biodiversity Areas	Impact	4	4	2	2	2	2	4	3	3	2	2	2	1	1	2	1	4	4	1	4	4	2	2	4	2	3
6.3	Other Important Delineated Areas	Impact	4	4	2	2	2	2	4	4	2	2	2	2	1	1	2	1	4	4	1	4	4	2	2	4	2	3
6.4	Ecosystem Condition	Impact	4	4	2	2	2	2	4	4	2	2	2	2	1	1	2	1	4	4	1	4	4	2	2	4	2	3
6.5	Range Rarity	Impact	3	3	1	1	1	1	3	3	3	1	3	1	0	0	1	2	3	3	0	3	3	2	1	2	2	2
7.1	Indigenous Peoples (IPs); Local Communities (LCs) Lands and Territories	Impact	5	5	3	3	3	3	3	5	3	3	3	3	1	1	3	1	5	5	1	5	5	3	3	5	3	3
7.2	Resource Scarcity: Food - Water - Air	Impact	3	3	1	1	1	1	1	1	0	1	2	2	1	0	1	3	1	2	0	2	0	0	2	1	1	1
7.3	Labor/Human Rights	Impact	4	4	2	2	2	2	2	2	2	2	4	2	2	2	2	4	4	4	2	4	2	2	4	2	2	3
7.4	Financial Inequality	Impact	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
8.1	Media Scrutiny	Dependency	5	5	3	1	4	4	2	2	2	1	5	5	3	3	1	3	4	5	3	4	1	1	3	1	5	3
8.2	Political Situation	Dependency	3	3	2	2	2	2	3	3	2	2	3	3	1	1	2	3	3	3	1	3	3	2	2	3	2	2
8.3	Sites of International Interest	Dependency	3	3	2	2	2	2	3	3	2	2	3	2	0	0	2	3	3	3	0	3	3	2	2	3	2	2
8.4	Risk Preparation	Dependency	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2

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APPENDIX 0.3: WWF BRF RISK HIERARCHY

Table 8: Four-level hierarchy of the biodiversity risk assessment framework

Risk type	Risk category	Risk indicator	Metrics
Physical Risk	Provisioning Services	Water Scarcity	Water Scarcity
		Forest Productivity and Distance to Markets	Realisable Hard and Soft Commercial Timber
		Limited Wild Flora & Fauna Availability	Global Centers of Unsustainable Commercial Harvesting of Species
		Limited Marine Fish Availability	Stock Status
	Regulating & Supporting Services - Enabling	Soil Condition	Soil Organic Carbon
		Water Condition	Freshwater Quality
			Marine Water Quality
		Air Condition	PM2.5 Concentrations
		Ecosystem Condition	Ecosystem Intactness & Connectivity (Terrestrial)
			Ecosystem Connectivity (Freshwater)
			Ecosystem Intactness (Marine)
		Pollination	Crop Pollination
	Regulating Services – Mitigating	Landslides	Landslide Hazard
		Wildfire Hazard	Wildfire Hazard
		Plant/Forest/Aquatic Pests and Diseases	Frequency of Plant/Forest/Aquatic Pests and Diseases
		Herbicide Resistance	Antimicrobial and Agrochemical Resistances
		Extreme Heat	Extreme Heat Hazard
		Tropical Cyclones	Tropical Cyclonic Wind and Storm Surge Hazard
	Cultural Services	Tourism Attractiveness	Tourism Demand Drivers (Natural and Cultural)
	Pressures on Biodiversity	Land, Freshwater and Sea Use Change	Cropland Expansion (Terrestrial)
			Fragmentation of Rivers (Freshwater)
			Direct Human Impact & Fishing (Marine)
		Tree Cover Loss	Tree Cover Loss
		Invasives	Presence of Invasives
		Pollution	Terrestrial Nutrient Pollution
			Terrestrial Pesticide Pollution
			Freshwater Nutrient Pollution
			Marine Nutrient Pollution
			Marine Pesticide Pollution
			Air Pollution
Reputational Risk	Environmental Factors	Protected/Conserved Areas	Protected Areas
		Key Biodiversity Areas	Key Biodiversity Areas
		Other Important Delineated Areas	Intact Forest Landscapes
			WWF's Global 200
			Ecologically or Biologically Significant Marine Areas
			Vulnerable Marine Ecosystems
		Ecosystem Condition	Ecosystem Intactness & Connectivity (Terrestrial)
			Ecosystem Connectivity (Freshwater)
			Ecosystem Intactness (Marine)
		Range Rarity	Range Rarity
	Socioeconomic Factors	Indigenous Peoples (IPs); Local Communities (LCs) Lands and Territories	No Data
		Resource Scarcity: Food - Water - Air	Food Security
			Water Scarcity
			Air Condition
		Labor/Human Rights	Ratified International Human Rights Instruments
			Labor Rights Violations
		Financial Inequality	Financial Inequality
	Additional Reputational Factors	Media Scrutiny	Media Scrutiny (Ecological Topics)
			Media Scrutiny (Social Topics)
		Political Situation	Violence Against Land and Environmental Defenders
			Freedom
			Governance
			Corruption
		Sites of International Interest	Natural World Heritage Sites
			RAMSAR Sites
		Risk Preparation	Index of Risk Preparation

APPENDIX 0.4: BIODIVERSITY IMPORTANCE AND INTEGRITY INDICATORS

The 56 data sets that were used to create importance and integrity scores for the 33 different indicators are described in detail below, including information on the rationale, the thresholds for the risk-score classification and data sources.

1. PHYSICAL RISK INDICATORS

Physical risk is driven by the ways in which a company depends on nature and can be affected by both natural and human-induced changes to the condition of land- and seascapes. It comprises the following risk categories: 1) Provisioning Services; 2) Regulating & Supporting Services - Enabling; 3) Regulating Services - Mitigating; 4) Cultural Services; and 5) Pressures on Biodiversity. Therefore, physical risks account for the status of the ecosystem services that companies, or their suppliers, rely on.

1 – Provisioning Services

Many industries or companies rely directly on the provisioning of natural inputs for their operations or production. As such, declines due to ecosystem service degradation in the quantity or quality of direct inputs for feed, raw materials, genetic materials, etc. can result in increased costs or disruption of production. This risk category identifies the main categories of natural resources needed for production. This risk category within the BRF comprises the risk indicators: 1) Water Scarcity, 2) Forest Productivity and Distance to Markets, 3) Limited Wild Flora & Fauna Availability, and 4) Limited Marine Fish Availability.

1.1 – Water Scarcity

1.1.1 – Water Scarcity

Water scarcity refers to the physical abundance or lack of freshwater resources, which can significantly impact a company through production or supply chain disruption, higher operating costs and growth constraints. Water scarcity is human-driven and can be aggravated by natural conditions (e.g., aridity, drought). It is generally calculated as a function of the volume of water used relative to the volume of water available in a given area.

This indicator has already been calculated in the WWF WRF and has been integrated into the WWF BRF without changes. The WWF WRF water scarcity risk category is a comprehensive and robust metric as it integrates a total of seven best available and peer-reviewed data sets covering different aspects of scarcity, as well as different modelling approaches: aridity index, water depletion, baseline water stress, blue water scarcity, available water remaining, drought frequency probability and projected change in drought occurrence. For more information, please consult the *Water Risk Filter Methodology* or visit the *Water Risk Filter* directly.

1.2 – Forest Productivity and Distance to Markets

1.2.1 – Realisable Hard and Soft Commercial Timber

Realised hard and soft commercial timber value. Model results from the costing nature version 3 policy support system (Mulligan M. , 2021) has been used as the basis to estimate the availability and commercial accessibility of wood-based fibres and timber. Please note that this is a global indicator and may not be applicable in certain conditions, e.g. in sparsely populated areas such as some boreal regions and for plantations with connection to infrastructure that is independent of population centers.

Timber provision is critical for activities such as house building, furniture manufacture, food storage and water and agricultural infrastructure. At low extraction rates, it is sustainable and can continue to be provided at the rates consumed. At high extraction rates, it is consumptive of the ecosystem and may damage co-benefits for other services provided by forests. Realised timber services thus need to be considered carefully in this regard. Timber is separated into commercial timber and domestic timber. Commercial timber contributes value to national beneficiaries, whereas domestic timber contributes value to local beneficiaries. Only the former has been considered in this analysis.

For commercial timber, the first step is to estimate the potential mass of timber (the potential service) from the above-ground carbon stock map (Ruesch & Gibbs, 2008; Saatchi, et al., 2011). The proportion of carbon coming from trees in a pixel is calculated as the product of carbon stock and fractional tree cover (Copernicus, 2015) for rural areas only (Schneider, Friedl, & Potere, 2009), as urban trees are considered not to be usable for timber. The sustainable harvest is considered to be the reciprocal of the number of years taken to develop the stock at the annual sequestration rate, according to the dry matter productivity data of (Mulligan M. , 2018), based on a 10-year climatology of SPOT VGT data.

Softwood and hardwood are also considered since these have differing economic values. The spatial distribution of hardwood and softwood is calculated according to the work of Box and Fujiwara (Box & Kazue, 2013), in which mean annual temperature and a cold index are calculated from mean monthly temperatures (Hijmans, Cameron, Parra, Jones, & Jarvis, 2005). The cold index is the sum of temperature for months where temperatures are less than 5°C. Hardwood distributions are calculated as those with a mean annual temperature above 20°C and a cold index above -10°C. Softwood areas are calculated as all other areas.

To calculate the relative realised timber services indexes (RRTS), the realised service (the timber accessible) is calculated as potential timber within six hours travel time of a population centre of greater 50,000 people and on slope gradients below 31.5 degrees (70 per cent) (Lehner, Verdin, & Jarvis, 2008), which are considered to be workable for logging (Greulich, Hanley, McNell, & Baumgartner, 1999). This accessibility requirement represents the availability of transport infrastructure for timber. Timber mass defined as accessible is constrained by slope to reflect the higher cost of removal and increased wastage on steeper slopes, using a linear decrease in timber availability (from the potential availability to zero) as slope increases from 0 to 90 degrees. The product of the potential services and these accessibility constraints is the realised timber service in tonnes.

To produce the WWF BRF indicator, the raw data was processed as follows: 1) the categorical raster data was aggregated to the HydroBASINS level 7 using the mean value; 2) it was then classified into the five risk-score classes, following the classification as in the table below.

Biodiversity Risk Filter risk score	Relative realised timber services indices (RRTS)
1 - Very low risk	>0.18-1
2 - Low risk	>0.066-0.18
3 - Moderate risk	>0.0053-0.066
4 - High risk	>0-0.0053
5 - Very high risk	0

1.3 – Limited Wild Flora & Fauna Availability

1.3.1 – Global Centers of Unsustainable Commercial Harvesting of Species

Non-timber wild plants are used in many applications, including for medicinal, cosmetic, aromatic and genetic purposes. They are used globally as feed, fibre (e.g., for clothing, building materials, etc.), fuel, medicines and food ingredients (Jenkins, Timoshyna, & Cornthwaite, 2018). Overexploitation is one of the main threats to nature, but the intensity of this threat varies geographically. To estimate availability of wild flora and fauna, De Minin E. et al.’s (2019) global centres of unsustainable commercial harvest paper has been used. The paper identified global concentrations, on land and at sea, of 4,543 species threatened by unsustainable commercial harvesting, to identify regions under threat.

To produce the WWF BRF indicator, the raw data was processed as follows: 1) the categorical raster data was aggregated to the assessment unit level using the max value; 2) and it was then classified into the five risk-score classes, following the classification as in the table below.

Biodiversity Risk Filter risk score	Intensity of unsustainable commercial harvesting
1 - Very low risk	
2 - Low risk	
3 - Moderate risk	Unknown intensity of unsustainable commercial harvesting
4 - High risk	
5 - Very high risk	High intensity of unsustainable commercial harvesting

1.4 – Limited Marine Fish Availability

1.4.1 – Stock Status

As the largest traded food commodity in the world, seafood provides sustenance to billions of people worldwide (WWF, 2022b). Nowadays, more than 85 per cent of the world's fisheries have been pushed to or beyond their biological limits. Overfishing occurs in areas that have been exploited at levels that exceed the capacity for replacement by reproduction and growth of the exploited species. Species that are being overfished are producing catches that are below the level that could be sustainably derived. As a result of intense exploitation, most fisheries generally follow sequential stages of development: undeveloped, developing, fully exploited, overfished and collapsed. The indicator measures the percentage of stocks categorized as rebuilding/collapsed/over-exploited/exploited as opposed to stocks that are categorized as developing (Sea Around Us, 2020).

To produce the WWF BRF indicator, the raw data was processed as follows: 1) the percentage of stocks categorized as rebuilding/collapsed/over-exploited/exploited per Exclusive Economic Zone were aggregated to Marine Ecoregions of the World using the mean value; 2) it was then classified into the five risk-score classes, following the classification as in the table below.

Biodiversity Risk Filter risk score	Percentage of stocks of categorized as rebuilding/collapsed/over-exploited/exploited
1 - Very low risk	<25%
2 - Low risk	>25-50%
3 - Moderate risk	>50-80
4 - High risk	>80-95
5 - Very high risk	>95%

2 – Regulating and supporting services – Enabling

Many companies rely on regulating and supporting ecosystem services that enable production processes, including the cultivation of crops or breeding of animals. Declines in enabling ecosystem services such as soil health, water quality and quantity and habitat provision can result in increased costs of production or an inability to operate. This risk category within the BRF comprises the risk indicators: 1) Soil Condition, 2) Water Condition, 3) Air Condition, 4) Ecosystem Condition and 5) Pollination.

2.1 – Soil Condition

2.1.1 – Soil Organic Carbon

Soil organic carbon (SOC) is the main component of soil organic matter (SOM) and is a prerequisite for food production, mitigation and adaptation to climate change and the achievement of the Sustainable Development Goals (SDGs). SOC affects most of the processes relevant to soil functions and food production. A high SOM and therefore SOC content provides plants with the nutrients and water they need by increasing soil fertility and water availability, which in turn improves food productivity. SOC has also long been used as an indicator of soil health, due to its capacity to improve soil structural stability, which affects porosity, aeration and water filtration capacities to supply clean water. However, SOC mineralisation can be an important source of greenhouse gas emissions. This means that changing SOM (and hence SOC) not only changes the provision of ecosystem services required for crop production, but also affects the capacity of soils to buffer against environmental changes, as it regulates the resilience of agricultural systems to climate change (FAO; ITPS, 2018).

GSOCmap (FAO, 2019) is the first global SOC map, produced through a consultative and participatory process involving Global Soil Partnership member countries, which makes this map unique. The map was prepared by member countries under the guidance of the Intergovernmental Technical Panel on Soils and the Global Soil Partnership Secretariat. Countries agreed on the methodology used to produce the map and were trained on modern tools and methodologies to develop national maps. The Global Soil Partnership then gathered all national maps to produce the final product, ensuring a thorough harmonisation process.

To produce the WWF BRF indicator, the raw data was processed as follows: 1) the categorical raster data was aggregated to the HydroBASIN level 7 using the mean value; 2) it was then classified into the five risk-score classes, following the classification as in the table below.

Biodiversity Risk Filter risk score	Average SOC tonnes/ha
1 - Very low risk	>90
2 - Low risk	>70-90
3 - Moderate risk	>50-70
4 - High risk	>30-50
5 - Very high risk	<=30

2.2 – Water Condition

Water quality indicates whether water resources are fit for use by humans and ecosystems alike. Poor water quality – water pollution – can impact a company indirectly by destabilising ecosystems or by causing serious health issues, as well as directly through increased operating costs and a reduction in production or growth.

The water condition indicator has been calculated separately for freshwater and marine areas.

2.2.1 – Freshwater Quality

This indicator has already been calculated in the Water Risk Filter and has been integrated here without changes. The Water Risk Filter risk category water quality considers parameters with well-documented direct and indirect negative effects on water security for both humans and freshwater nature, which are aligned to SDG 6.3.2: biological oxygen demand (BOD) as a widely used umbrella proxy for overall water quality; electrical conductivity (EC) as a proxy for salinity balance and pH alteration; and nitrogen, to capture nutrient loading in water bodies. For more information, please consult the Water Risk Filter Methodology or visit the Water Risk Filter website directly.

2.2.2 – Marine Water Quality

Marine water quality was estimated using three data sets: Ocean Health Index nutrient pollution data (Halpern, et al., 2012); ocean acidification data sets (Halpern, et al., 2012); and the WRI's Eutrophication and Hypoxia data set (Diaz, Selman, & Chique, 2011).

To produce the BRF indicator, the raw data was processed as follows: 1) the hypoxia, nutrient pollution and acidification data was aggregated to the FAO Statistical Fishing Areas and Marine Ecoregions of the World using the mean value; 2) it was then classified into the five risk-score classes, following the classification as in the tables below. Finally, the risk score for marine water quality was derived from the mean of the hypoxia, nutrient pollution and acidification risk scores.

Biodiversity Risk Filter risk score	# of hypoxia events
1 - Very low risk	0
2 - Low risk	1
3 - Moderate risk	2-3
4 - High risk	4-10
5 - Very high risk	>10

Biodiversity Risk Filter risk score	Nutrient pollution (0-1)
1 - Very low risk	0
2 - Low risk	>0.000001-0.001758
3 - Moderate risk	>0.001759-0.007936
4 - High risk	>0.007937-0.026952
5 - Very high risk	> 0.026953

Biodiversity Risk Filter risk score	Acidification as the difference of the aragonite saturation state (Ωarag) in the pre-industrial era and modern times
1 - Very low risk	0.144533-0.192124
2 - Low risk	0.192125-0.201112
3 - Moderate risk	0.201113-0.224868
4 - High risk	0.224869-0.290256
5 - Very high risk	>0.290257

2.3 – Air Condition

2.3.1 – PM2.5 Concentrations

(Hammer, 2022) measured the annual global surface of concentrations (micrograms per cubic metre) of all composition ground-level fine particulate matter of 2.5 micrometres or smaller (PM2.5) for large-scale health and environmental research by combining Aerosol Optical Depth retrievals from multiple satellite algorithms including the NASA MODerate resolution Imaging Spectroradiometer Collection 6.1 (MODIS C6.1), Multi-angle Imaging SpectroRadiometer Version 23 (MISRv23), MODIS Multi-Angle Implementation of Atmospheric Correction Collection 6 (MAIAC C6) and the Sea-Viewing Wide Field-of-View Sensor (SeaWiFS) Deep Blue Version 4. The data set is used as a proxy for air quality, as exposure to high average concentrations of PM2.5 over time has been a reliable predictor of heightened mortality (Health Effects Institue, 2020).

To produce the Biodiversity Risk Filter indicator, the raw data was processed as follows: the categorical raster data was aggregated to the HydroBASIN level 7 using the mean value; 2) it was then classified into the five risk-score classes, following the classification as in the table below.

Biodiversity Risk Filter risk score	Concentrations (micrograms per cubic metre) of all composition ground-level fine particulate matter of 2.5 micrometres or smaller (PM2.5)
1 – Very low risk	<7
2 – Low risk	>7-12
3 – Moderate risk	>12-22
4 – High risk	>22-50
5 – Very high risk	>50

2.4 – Ecosystem Condition

Natural habitats provide a wide array of ecosystem services that are important to companies, people and communities, such as climate and streamflow regulation, water purification, species habitat maintenance, regulation/buffering of pests and diseases, pollination, maintenance of soil structure and fertility, nutrient cycling and hydrological services and indigenous cultural practices, among many others (Beyer, Venter, Grantham, & Watson, 2020). The degradation of natural habitats can therefore result in restricted access to the enablers on which companies and people rely.

The preservation and restoration of terrestrial, freshwater and marine habitats is a key component in addressing biodiversity risk and in the achievement of the SDGs.

2.4.1 – Ecosystem Intactness & Connectivity (Terrestrial)

To calculate terrestrial ecosystem intactness, the Biodiversity Intactness Index (BII) (Natural History Museum, 2016) was used in combination with the Functional Connectivity of the World's Protected Areas (Brennan, et.al. 2022).

1) The BII is the modelled average abundance of originally present species, relative to their abundance in an intact ecosystem. It functions as a global estimate of how pressures have affected the numbers of species and individuals found in samples from local terrestrial ecological assemblages.
2) Functional Connectivity of the World's Protected Areas (Brennan, et al., 2022) maps the functional connectivity (how mammals move through landscapes) of the world's terrestrial protected areas. This data set is the first of its kind to describe connectivity currents globally. It is used as a proxy for changes in the spatial configuration of the landscape.

To produce the Biodiversity Risk Filter indicator, the raw data was processed as follows: 1) the BII and Connectivity data were aggregated to the HydroBASINS level 7 using the mean value; 2) it was then classified into the five risk-score classes, following the classification as in the tables below. 3) Finally, a risk score was created for terrestrial intactness & connectivity by calculating the mean of the BII and connectivity risk scores.

Biodiversity Risk Filter risk score	2005 Biodiversity Intactness (%)
1 - Very low risk	>97.5
2 - Low risk	>90-97.5
3 - Moderate risk	>80-90
4 - High risk	>70-80
5 - Very high risk	<=70

Biodiversity Risk Filter risk score	Mammal movement probability (MMP)
1 - Very low risk	>2,070 (Very high connectivity)
2 - Low risk	>1,240-2070 (High connectivity)
3 - Moderate risk	>825-1,240 (Medium connectivity)
4 - High risk	>415-825 (Low connectivity)
5 - Very high risk	0-415 (Very low connectivity)

2.4.2 - Connectivity (Freshwater)

This indicator has already been calculated in the Water Risk Filter (4.1. Fragmentation Status of Rivers) and has been integrated into the Biodiversity Risk Filter without changes. For more information, please consult the Water Risk Filter methodology or visit the Water Risk Filter directly.

2.4.2 – Ecosystem Intactness (Marine)

To calculate marine habitat conditions, Ocean Health Index habitat condition data was considered for six marine ecosystems: coral, mangrove, sea ice, sea grass, salt marsh and softbottom habitat (Halpern, et al., 2012).

To produce the Biodiversity Risk Filter indicator, the raw data was processed as follows: 1) an average value was calculated for marine habitat condition from the habitat conditions of coral, mangrove, sea ice, sea grass, salt marsh and softbottom; 2) the resulting habitat condition average was aggregated to the FAO Statistical Fishing Areas and Marine Ecoregions of the World using the mean value; 3) this was then classified into the five risk-score classes, following the classification as in the table below.

Biodiversity Risk Filter risk score	Habitat condition (%)
1 – Very low risk	100
2 – Low risk	>92-99
3 – Moderate risk	>86-92
4 – High risk	>82.2-86
5 – Very high risk	<=86

2.5 – Pollination

2.5.1 – Crop Pollination

Up to two-thirds of all crops require some degree of animal pollination to reach their maximum yields, and natural habitat around farmlands can support healthy populations of wild pollinators by providing them with foraging and nesting resources.

As part of the mapping of the planet's critical natural assets for people (NCP) (Chaplin Kramer, et al., 2020), the crop pollination data set models the potential contribution of wild pollinators to nutrition production, based on pollination sufficiency of habitat surrounding farmland and the pollination dependency of crops. NCP for crop pollination is expressed in terms of the average equivalent number of people fed by pollination-dependent crops, attributed to nearby ecosystems based on the area of pollinator habitat within pollinator flight distance of crops. It measures how much nutrition is produced on fields that are dependent on the surrounding natural habitat to sustain pollination.[33]

To produce the Biodiversity Risk Filter indicator, the raw data was processed as follows: 1) the categorical raster data was aggregated to the HydroBASINS level 7 using the mean value; 2) it was then classified into the five risk-score classes, following the classification as in the table below.

Biodiversity Risk Filter risk score	Equivalent people fed
1 - Very low risk	0-0.0004
2 - Low risk	>0.0004-0.008
3 - Moderate risk	>0.008-1.5
4 - High risk	>1.5-2.7
5 - Very high risk	>2.7

3. Regulating Services – Mitigating

The occurrence of natural hazards such as landslides, fires and storms can disturb or disrupt projects, operations, or entire value chains, and in some cases can result in severe damage to or loss of assets. Intact ecosystems can help to mitigate the impact of some natural hazards. This risk category within the BRF comprises the risk indicators: 1) Landslides, 2) Forest Canopy Loss, 3) Invasives and 4) Pollution.

3.1 – Landslides

3.1.1 – Landslide Hazard

Landslides impose significant risks to human lives and economic activities. Landslides have become more prevalent because of anthropogenic disturbances, such as land-cover changes, land degradation and expansion of infrastructure. These are further exacerbated by more extreme precipitation due to climate change, which is predicted to trigger more landslides and threaten sustainable development in vulnerable regions (Binbin, Clinton, Xu, & Weihua, 2021).

The Global Landslide Hazard Map has been used as the basis for this indicator. It presents a qualitative representation of global landslide hazard at a global scale. It is a combination of the Global Landslide Hazard Map: Median Annual Rainfall-Triggered Landslide Hazard (1980-2018) and the Global Landslide Hazard Map: Earthquake-Triggered Landslide Hazard, which has then been simplified to four categories, ranging from very low to high landslide hazard (GFDRR, 2020).

To produce the Biodiversity Risk Filter indicator, the raw data was processed as follows: 1) the categorical raster data was aggregated to the HydroBASINS level 7 using the mean value; 2) it was then classified into the five risk-score classes, following the classification as in the table below.

Biodiversity Risk Filter risk score	Landslide hazard categories
1 - Very low risk	1
2 - Low risk	2
3 - Moderate risk	
4 - High risk	3
5 - Very high risk	4

33 As an example, consider two fields of equal size, one surrounded by one acre of natural habitat, the other by 10 acres of natural habitat. The first field will have more 'equivalent people fed' per acre of natural habitat. However, the first field is under more risk, because if the acre of natural habitat is destroyed, the field will have no pollinators: higher equivalent people fed means higher dependency and therefore higher risk.

3.2 – Wildfire Hazard

3.2.1 – Global Wildfire Hazard

This indicator is based on the Global Facility for Disaster Reduction and Recovery's (GFDRR) global wildfire hazard levels (GFDRR, 2017c). The approach to classifying wildfire hazard levels used is based solely on fire weather index climatology. Fire weather indexes are used in many countries to assess both the onset of conditions that will enable fires to spread, as well as the likelihood of fire at any point in the landscape. The method presented uses statistical modelling (extreme value analysis) of a 30-year fire weather climatology to assess the predicted fire weather intensity for a 10-year return period interval. These intensities are classified based on thresholds using conventions to provide hazard classes that correspond to conditions that can support problematic fire spread in the landscape, if an ignition and sufficient fuel were to be present.

To produce the Biodiversity Risk Filter indicator, the raw data was processed as follows: 1) the categorical raster data was aggregated to the HydroBASINS level 7 using the mean value; 2) it was then classified into the five risk-score classes, following the classification as in the table below.

Biodiversity Risk Filter risk score	Maximum predicted fire weather intensity for a 10-year return period
1 - Very low risk	>0-15
2 - Low risk	>15-30
3 - Moderate risk	>30-60
4 - High risk	>60-120
5 - Very high risk	>120

3.3 – Plant/Forest/Aquatic Pests and Diseases

3.3.1 – Frequency of Plant/Forest/Aquatic Pests and Diseases

As genetic and species diversity is lost and ecosystems are degraded, the complexity of the overall system can be compromised, making it more vulnerable and potentially creating new opportunities for disease emergence and poor health outcomes in humans, livestock and wildlife (World Health Organization, 2022). This increases risks to economic activity, as well as risks of epidemics and pandemics. Emerging diseases include transboundary animal and plant pests and diseases, including forest/timber pests and aquatic animal diseases. Food safety threats can have a large impact on food security, human health, livelihoods and trade (FAO, 2020b).

To estimate the frequency of zoonotic, vector-borne and water-borne diseases, data from the FAO's Food Chain Crisis Early Warning Bulletin (2018-2020) was used. The purpose of the bulletin is to inform of forecasted threats to animal and plant health and food safety that may have a significant impact on food and nutrition security for the three months ahead. Please note that the source data for this indicator is only available on a country level.

To produce the Biodiversity Risk Filter indicator, the raw data was processed as follows: 1) the total number of forecasted threats was counted between 2018 and 2020 per country, 2) country data was aggregated to the HydroBASINS level 7 using the majority value; 3) it was then classified into the five risk-score classes, following the classification as in the table below.

Biodiversity Risk Filter risks score	Number of forecasted transboundary animal and plant pests and diseases
1 - Very low risk	0-1
2 - Low risk	2-8
3 - Moderate risk	9-21
4 - High risk	22-42
5 - Very high risk	>42

3.4 – Herbicide Resistance

3.4.1 – Antimicrobial and Agrochemical Resistances

Herbicide resistance is the ability of a weed to survive a herbicide application that had been used to contain that population. As unwanted plants compete with crops, issues of crop loss and contamination arise.

To estimate antimicrobial and agrochemical resistance, data from the Weed resistance database (International Survey of Herbicide Resistant Weeds) was used (Heap, 2021).

The International Survey of Herbicide Resistant Weeds is a collaborative effort between weed scientists in over 80 countries with the aim of maintaining scientific accuracy in the reporting of herbicide resistant weeds globally. Please note that the source data for this indicator is only available on a country level.
To produce the Biodiversity Risk Filter indicator, the raw data was processed as follows: 1) the number of occurrences of herbicide resistant weeds was tallied from the weed resistance database; 2) the count by country was aggregated to the HydroBASIN level 7 using the majority value; 3) it was then classified into the five risk-score classes, following the classification as in the table below.

Biodiversity Risk Filter risk score	Number of occurrences of herbicide resistant weed
1 - Very low risk	0
2 - Low risk	1-15
3 - Moderate risk	16-28
4 - High risk	29-45
5 - Very high risk	>45

3.5 – Extreme Heat

3.5.1 – Extreme Heat Hazard

Extreme heat has an obvious impact on human health, but it is also relevant to all kinds of projects and sectors, including the built environment, as heat stress affects people using buildings and infrastructure, therefore influencing their design.

GFDRR's extreme heat hazard is classified based on an existing and widely accepted heat-stress indicator, the wet bulb globe temperature (WBGT, in °C) – more specifically the daily maximum WGBT. A short return period (five years) reflects more frequent extreme heat events (GFDRR, 2017b).

With climate change, the frequency and the intensity of abnormal weather and extreme temperature patterns have dramatically increased, and the shift to warmer temperatures, driven by climate change, will only exacerbate this phenomenon (Betrand & Parnaudeau, 2017).

To produce the Biodiversity Risk Filter indicator, the raw data was processed as follows: 1) the categorical raster data was aggregated to the HydroBASINS level 7 using the mean value; 2) it was then classified into the five risk-score classes, following the classification as in the table below.

Biodiversity Risk Filter risk score	Daily maximum wet bulb globe temperature (WBGT, in °C) – 5yr return period
1 - Very low risk	<24
2 - Low risk	24-28
3 - Moderate risk	28-30
4 - High risk	30-32
5 - Very high risk	>32

3.6 Tropical Cyclones

3.6.1 – Tropical Cyclonic Wind and Storm Surge Hazard

Storms can impact companies and value chains through a variety of ways, including building and property damage, flooding or power outages, which may lead to temporary or permanent company closures and loss of revenue.

This indicator is based on GFDRR's tropical cyclonic strong wind and storm surge model, using information from 2,594 historical tropical cyclones, topography, terrain roughness and bathymetry. The historical tropical cyclones used in the GAR15 cyclone wind and storm surge model are from five different oceanic basins: Northeast Pacific, Northwest Pacific, South Pacific, North Indian, South Indian and North Atlantic, with the tracks of the storms obtained from the IBTrACS database (Knapp, Kruk, Levinson, Diamond, & Neumann, 2010). This database is the most up-to-date repository of information associated with tropical cyclones.

Topography information was taken from NASA's Shuttle Radar Topography Mission (SRTM), which provides terrain elevation grids at a 90-metre resolution, delivered by quadrants around the world.
To account for surface roughness, polygons of urban areas worldwide were obtained from the Socioeconomic Data and Applications Centre, SEDAC (2011). This was considered a good proxy for the spatial variation of surface roughness.

A digital bathymetry model is employed with a spatial resolution of 30 arc-seconds, taken from the GEBCO_08 (General Bathymetric Chart of the Oceans) Grid Database of the British Oceanographic Data Centre (GEBCO, 2009). Bathymetry relates to information about the ocean floor, which has direct influence on the formation of storm surges. More information about the cyclone wind and storm surge hazard can be found in CIMNE (CIMNE-INGENIAR, 2015).

Hazard analysis was performed using the software CAPRA Team Tropical Cyclones Hazard Modeler (Cardona, et al., 2014). The vulnerability models used in the risk calculation for GAR correlate loss to wind speed for three-second gusts. For GAR15, the risk was calculated with the CAPRA-GIS platform, which is a risk modelling tool within the CAPRA suite (www.ecapra.org). The risk assessment was also conducted by CIMNE and Ingeniar, to produce AAL and PML values for cyclone risk (GFDRR, 2017a).
To produce the Biodiversity Risk Filter indicator, the raw data was processed as follows: 1) the categorical raster data was aggregated to the HydroBASINS level 7 using the mean value; 2) it was then classified into the five risk-score classes, following the classification as in the table below.

Biodiversity Risk Filter risk score	Predicted maximum wind speed (mph)– 50-year return period
1 - Very low risk	0
2 - Low risk	<60
3 - Moderate risk	>60-80
4 - High risk	>80-120
5 - Very high risk	>120

4 – Cultural Services

4.1 – Tourism Attractiveness

4.1.1 – Tourism Demand Drivers (Natural + Cultural)

Some industries, such as tourism, real estate and education, can depend highly on the presence of culturally valuable land or seascapes or specific sites. Tourism is an engine for jobs and investment. The degradation or loss of key attractive features in an area can negatively impact companies that rely on them. Nature-based tourism (NBT) is a sub-sector of the tourism industry that includes wildlife-based tourism, such as viewing, photographing, feeding and hunting (World Bank, 2018). The loss of key species upon which wildlife-based tourism is dependent would be catastrophic to NBT.

The Travel and Tourism Demand Drivers subindex of WEF's Travel & Tourism Development Index 2021 Edition captures the principal "reasons to travel" (WEF, 2021). For the BRF analysis, natural resource indicators and cultural resource indicators were included.

The natural resources pillar measures the available natural capital as well as the development of outdoor tourism activities. Countries with natural assets may be better positioned to attract tourists.

In this pillar, we include several attractiveness measures, including the number of UN Educational, Cultural and Scientific Organisation (UNESCO) natural World Heritage sites, the richness of fauna and biodiversity in the country and the scope of protected areas, which indicates the extent of national parks and nature reserves. Digital demand for nature and relevant activities is also measured as an illustration of how well known and effectively marketed a country's natural assets are.

The cultural resource pillar measures the availability of cultural resources such as archaeological sites and entertainment facilities. To an extent, this pillar captures how cultural resources are protected, developed and promoted. Included here are the number of UNESCO cultural World Heritage Sites, the number of large stadiums that can host significant sport or entertainment events and a measure of Digital Demand for a country's cultural sites and entertainment. Also included are the number of UNESCO Creative Cities, representing efforts to protect and develop cultural and creative activities and industries in urban centres. Please note that the source data for this indicator is only available on a country level.

To produce the Biodiversity Risk Filter indicator the raw data was processed as follows: 1) Create a mean score of both pillars (natural and cultural resource scores) 2) aggregate the country data to the HydroBASINS level 7 as well as the Marine Ecoregions of the World associated with each country's Exclusive Economic Zones using the mean value; 3) classify it into the 5 risk score classes, following the classification, as in the table below.

Biodiversity Risk Filter Risk Score	Mean Natural and Cultural Resource Score
1 - Very Low Risk	>6.2
2 - Low Risk	<=6.2
3 - Moderate Risk	<=5.2
4 - High Risk	<=4.5
5 - Very High Risk	<=3.4

5 – Pressures on Biodiversity

Direct drivers or pressures are drivers that unequivocally influence biodiversity and ecosystem processes (IPBES, 2017). This risk category within the BRF comprises the risk indicators: 1) Land, Freshwater and Sea Use Change, 2) Forest Canopy Loss, 3) Invasives and 4) Pollution.

5.1 – Land, Freshwater and Sea Use Change

Land-use change is the major human influence on habitats and can include the conversion of land cover (e.g. expansion of cropland), changes in the spatial configuration of the landscape (e.g. fragmentation of habitats) or changes in the management of the ecosystem or agro-ecosystem (e.g. through the intensification of agricultural management or forest harvesting) (IPBES, 2017). Here, we only include metrics for the first two, as there is currently no available global data set for changes in the management of ecosystems or agro-ecosystems.

5.1.1 – Cropland Expansion (Terrestrial)

To calculate this indicator Potapov's Global maps of cropland extent gain were used to assess conversion of land cover (Potapov, Turubanova, & Hansen, 2022). Please note that forest canopy loss (another important aspect of land-use change) is covered in indicator 5.2.2 **although we recognize that a significant amount of forest loss is caused by cropland expansion.**

To produce the Biodiversity Risk Filter indicator, the raw data was processed as follows: 1) the Global maps of cropland extent were aggregated to the HydroBASINS level 7 using the mean value; 2) it was then classified into the five risk-score classes, following the classification as in the tables below. 3) Finally, a risk score was created for terrestrial modification by calculating the mean of the change in cropland extent.

Biodiversity Risk Filter risk score	Percentage of cropland expansion between 2000 and 2019
1 - Very low risk	0-1
2 - Low risk	>1-3
3 - Moderate risk	>3-6
4 - High risk	>6-12
5 - Very high risk	>12

5.1.2 – Fragmentation of Rivers (Freshwater)

This indicator has already been calculated in the Water Risk Filter (4.1. Fragmentation Status of Rivers) and has been integrated into the Biodiversity Risk Filter without changes. For more information, please consult the Water Risk Filter methodology or visit the Water Risk Filter directly.

5.1.3 – Direct Human Impact & Fishing (Marine)

Halpern et.al. (2019) produced a shipping and direct human impact score as part of their analysis on human impact on the world's oceans (Halpern, et al., 2019). Fishing is included here as many fishing techniques (e.g., demersal fishing) have the potential to alter the sea floor and the natural marine environment. In a future iteration of the tool, this may also be included as a pressure on biodiversity through overexploitation of marine fish.

To produce the Biodiversity Risk Filter indicator, the raw data was processed as follows: 1) the shipping impact score and the direct human impact score were aggregated to the FAO Statistical Fishing Areas and Marine Ecoregions of the World using the mean value; 2) it was then classified into the five risk-score classes, following the classification as in the tables below. 3) Finally, the higher of the two scores was chosen.

Biodiversity Risk Filter risk score	Shipping impact score
1 - Very low risk	0-0.056608
2 - Low risk	0.056609-0.138555
3 - Moderate risk	0.138556-0.251314
4 - High risk	0.251315-0.398667
5 - Very high risk	0.398668-0.606808

Biodiversity Risk Filter risk score	Direct human impact score
1 - Very low risk	0-0.002793
2 - Low risk	0.002794-0.007965
3 - Moderate risk	0.007966-0.014956
4 - High risk	0.014957-0.032081
5 - Very high risk	0.032082-0.156244

5.2 – Tree Cover Loss

5.2.1 – Tree Cover Loss

Hansen et al. examined global Landsat data at a 30-metre spatial resolution to characterise tree cover extent, loss and gain from 2000 to 2021 (Hansen, et al., 2021). Tree cover loss was defined as a stand-replacement disturbance or the complete removal of tree cover at the Landsat pixel scale (30m). Recently harvestedareas using clear cutting practices are thus included. For this indicator, only tree cover loss since 2020 was taken into account. To produce the Biodiversity Risk Filter indicator, the raw data was processed as follows: 1) the tree cover loss maps were aggregated to the HydroBASINS level 7 using the mean value; 2) it was then classified into the five risk-score classes, following the classification, as in the tables below.

Biodiversity Risk Filter risk score	Average tree cover loss in %
1 - Very low risk	0
2 - Low risk	>0 - 1%
3 - Moderate risk	>1-3%
4 - High risk	>3- 8%
5 - Very high risk	>8%

5.3 – Invasives

Invasive species may be indigenous and/or exotic or alien. They occur mostly in terrestrial and aquatic ecosystems, both marine and freshwater, and can disrupt the ecological functioning of natural systems. Invasive species can out-compete local and indigenous species for natural resources, with negative implications for biodiversity. Invasive and alien species have been reported around the world, resulting in loss of biodiversity at local and regional scales and causing significant economic damage (IPBES, 2017).

5.3.1 – Presence of Invasives

The basis for this indicator is the Invasive Species Specialist Group's Global Invasive Species Database, which lists 100 of the world's worst invasive alien species as well as in which countries they are considered invasive. Species were selected for the list according to two criteria: their serious impact on biological diversity and/or human activities and their illustration of important issues surrounding biological invasion. To ensure the inclusion of a wide variety of examples, only one species from each genus was selected. Absence from the list does not imply that a species poses a lesser threat (Global Invasive Species Database, 2022). Please note that the source data for this indicator is only available on a country level.

To produce the Biodiversity Risk Filter indicator, the raw data was processed as follows: 1) the number of the world's worst invasive alien species per country/marine unit was aggregated to the HydroBASINS level/marine assessment units, respectively; 2) it was then classified into the five risk-score classes, following the classification as in the tables below.

Terrestrial Biodiversity Risk Filter risk score	# of world's worst invasive alien species
1 - Very low risk	<=5
2 - Low risk	>5-15
3 - Moderate risk	>15-25
4 - High risk	>25-45
5 - Very high risk	>45

Marine Biodiversity Risk Filter risk score	# of world's worst invasive alien species
1 - Very low risk	0
2 - Low risk	1
3 - Moderate risk	2
4 - High risk	3
5 - Very high risk	>4

5.4 – Pollution

Pollution is an important driver of biodiversity and ecosystem change throughout all biomes, with particularly devastating direct effects on freshwater and marine habitats (IPBES, 2017). The BRF only focuses on nutrient, pesticide and air pollution at this point. Further inclusions could be made, e.g. plastic and light and noise pollution, which can have a significant impact on biodiversity.

5.4.1 – Terrestrial Nutrient Pollution

At a global level, the atmospheric deposition of nitrogen has been recognised as one of the most important threats to the integrity of global biodiversity. Once nitrogen is deposited on terrestrial ecosystems, a cascade of effects can occur that often leads to overall declines in biodiversity. Within terrestrial biomes, nitrogen deposition through fossil fuels and fertiliser use has been found to impede decomposition and slow microbial growth, with a number of implications for terrestrial biodiversity (IPBES, 2017).

FAO provides data on total nitrogen per country as well as the total area of cropland per country, from which total nitrogen per hectare of cropland can be inferred (FAO, 2020a). Please note that the source data for this indicator is only available on a country level.

To produce the Biodiversity Risk Filter indicator, the raw data was processed as follows: 1) the nitrogen use per country was aggregated to the HydroBASINS level; 2) it was then classified into the five risk-score classes, following the classification as in the tables below.

Biodiversity Risk Filter risk score	Total nitrogen used (kg/ha)
1 - Very low risk	<14
2 - Low risk	>14-53
3 - Moderate risk	>53-72
4 - High risk	>72-77
5 - Very high risk	>77

5.4.2 – Terrestrial Pesticide Pollution

FAO provides county-level data on total pesticide use per country, as well as total area of cropland per country, from which total pesticide per hectare of cropland can be inferred (FAO, 2020c). Please note that the source data for this indicator is only available on a country level.

To produce the Biodiversity Risk Filter indicator, the raw data was processed as follows: 1) the pesticide use per country was aggregated to the HydroBASINS level 7; 2) it was then classified into the five risk-score classes, following the classification as in the tables below.

Biodiversity Risk Filter risk score	Total pesticides used (kg/ha)
1 - Very low risk	<0.73
2 - Low risk	0.73-4.2
3 - Moderate risk	>4.2-5.6
4 - High risk	>5.6-5.9
5 - Very high risk	>5.9

5.4.3 – Freshwater Nutrient Pollution

While terrestrial ecosystems have been affected by nitrogen-phosphorous fertilisers, these have had a far more pernicious effect on the biodiversity of freshwater and marine habitats, leading to eutrophication and hypoxic or 'dead' zones that support no aquatic life. Eutrophication and acidification occur when nitrogen and phosphorous are introduced, allowing algal blooms to proliferate which deplete the water of oxygen and which are frequently toxic (IPBES, 2017).

Using predictive models, McDowell et.al. projected median concentrations for total nitrogen concentrations during the growing season for catchments across the globe (McDowell, Noble, & Pletnvakov, 2020).
To produce the Biodiversity Risk Filter indicator, the raw data was processed as follows: 1) the total nitrogen concentration per HydroBASIN level 4 was aggregated to the HydroBASINS level 7; 2) it was then classified into the five risk-score classes, following the classification as in the tables below.

Biodiversity Risk Filter risk score	Total N concentration (mg/L)
1 - Very low risk	<=0.4
2 - Low risk	>0.4-0.8
3 - Moderate risk	>0.8-1.6
4 - High risk	>1.6-2.6
5 - Very high risk	>2.6

5.4.4 – Marine Nutrient Pollution

As with freshwater ecosystems, nitrogen and phosphorous pollution has led to eutrophication and hypoxic or 'dead' zones, caused by algal blooms (IPBES, 2017). Halpern et.al (2019) produced an impact score for nutrient pollution (from fertilizer runoff) as part of their analysis on human impact on the world's oceans (Halpern, et al., 2019).

To produce the Biodiversity Risk Filter indicator, the raw data was processed as follows: 1) the nutrient pollution impact score was aggregated to the FAO Statistical Fishing Areas and Marine Ecoregions of the World using the mean value; 2) it was then classified into the five risk-score classes, following the classification as in the tables below.

Biodiversity Risk Filter risk score	Nutrient pollution impact score
1 - Very low risk	0.000001-0.015
2 - Low risk	>0.015-0.042
3 - Moderate risk	>0.042-0.102
4 - High risk	>0.102-0.156
5 - Very high risk	>0.156

5.4.5 – Marine Pesticide Pollution

Halpern et.al (2019) produced an impact score for organic chemical pollution (from pesticide runoff) as part of their analysis on human impact on the world's oceans (Halpern, et al., 2019).

To produce the Biodiversity Risk Filter indicator, the raw data was processed as follows: 1) the organic chemical impact score was aggregated to the FAO Statistical Fishing Areas and Marine Ecoregions of the World using the mean value; 2) it was then classified into the five risk-score classes, following the classification as in the tables below.

Biodiversity Risk Filter risk score	Organic chemical pollution impact score
1 - Very low risk	<0.016
2 - Low risk	>0.016-0.049
3 - Moderate risk	>0.049-0.09
4 - High risk	>0.09-0.156
5 - Very high risk	>0.156

5.4.6 – Air Pollution

Please see indicator 2.3.1 – PM2.5 Concentrations

2. REPUTATIONAL RISK INDICATORS

Reputational risk can result from a company's actual or perceived impacts on nature and people. Reputational risk represents stakeholders' and local communities' perceptions of whether companies conduct business sustainably and responsibly with respect to biodiversity, and can ultimately affect brand value and market share, among other factors. Reputational risk is influenced both by operational factors (i.e., what a company does) and scape-based factors (i.e., the conditions of the places in which those operations occur). It comprises three risk categories: 1) Environmental Factors; 2) Socioeconomic Factors and 3) Additional Reputational Factors.

6 – Environmental Factors

Reputational risk can be driven by negative impacts on local environmental assets and the local prevalence of biodiversity-related issues. This risk category within the BRF comprises the risk indicators: 1) Protected/ Conserved Areas, 2) Key Biodiversity Areas, 3) Other Important Delineated Areas, 4) Ecosystem Condition and 5) Range Rarity.

6.1 – Protected/Conserved Areas

Protected and conserved areas have long been considered the cornerstones of biodiversity conservation (IPBES, 2019), and have an important role to play in achieving many of the Aichi global biodiversity targets and the SDGs (CBD, 2020) and in safeguarding the health of people and planet for generations to come (UNEP-WCMC and IUCN, 2021a). Currently the BRF only includes data on protected areas, as the global database on conserved areas (Other Area Based Effective Conservation Measures) is not yet globally representative.

6.1.1 – Protected Areas

For this indicator, UNEP-WCMC's World Database of Protected Areas (WDPA) (UNEP-WCMC and IUCN, 2021a) was used. It is the most authoritative source of data on protected areas globally.

We were generously given permission to utilise the WDPA data in the BRF by the Integrated Biodiversity Assessment Tool (IBAT) partners (IBAT, 2022).

To produce the BRF indicator, the raw data was processed as follows: 1) the per cent coverage was found for each assessment unit (terrestrial and marine) by protected area IUCN Category I – IV, as well as not-categorized protected areas; 2) the per cent coverage was found for each assessment unit (terrestrial and marine) by all other categories of protected area; 3) each assessment unit was classified into the five risk-score classes, following the classification as in the table on teh following page.

Biodiversity Risk Filter risk score	Based on % of assessment units overlapping with protected areas (PAs)
1 - Very low risk	0% overlap
2 - Low risk	>0-5% overlap with any PA
3 - Moderate risk	>5% overlap with any PA
4 - High risk	>5-30% overlap with PA I-IV + not categorzied
5 - Very high risk	>30% overlap with PA I-IV + not categorized

6.2 – Key Biodiversity Areas

6.2.1 – Key Biodiversity Areas

For this indicator, BirdLife International's World Database of Key Biodiversity Areas has been used (BirdLife International, 2022). Key biodiversity areas (KBAs) are the most important places in the world for species and their habitats. The KBA Programme supports the identification, mapping, monitoring and conservation of KBAs to help safeguard the most critical sites for nature on our planet – from rainforests to reefs, mountains to marshes, deserts to grasslands and to the deepest parts of the oceans (KBA, 2022).
We were generously given permission to utilise the KBA data in the BRF by the Integrated Biodiversity Assessment Tool (IBAT) partners (IBAT, 2022).

To produce the Biodiversity Risk Filter indicator, the raw data was processed as follows: 1) a 15km buffer around all global KBAs was created to account for any border discrepancies; 2) the per cent coverage of each assessment unit (terrestrial and marine) was found for all KBAs; 3) each assessment unit was classified into the five risk-score classes, following the classification as in the table below.

Biodiversity Risk Filter risk score	Based on % of assessment units overlapping with global Key Biodiversity Areas (KBA)
1 - Very low risk	no overlap with 15km buffer around KBA; No overlap with KBA
2 - Low risk	overlap with 15km buffer around KBA; No overlap with KBA
3 - Moderate risk	>0%-10% overlap with KBA
4 - High risk	>10%-50% overlap with KBA
5 - Very high risk	>50% overlap with KBA

6.3 – Other Important Delineated Areas

This sub-category is based on areas other than protected and conserved areas (PA) and Key Biodiversity Areas (KBA), which have been delineated due to their contribution to different aspects of biodiversity. Reputational risk will be influenced heavily by proximity to PAs and KBAs, particularly as these two designations are used in corporate and financial safeguards (e.g., IFC PS6). However, the delineation of these areas is not yet complete, being restricted by administrative, logistical and funding constraints. For example, KBAs must be identified 'bottom up' by local experts, using detailed local data, meaning that many sites exist that may meet the KBA criteria but have not yet been formally identified. In addition, while KBAs represent the most significant sites for the global persistence of biodiversity, other areas of importance are highly important regionally or nationally, and for particular biomes such as marine or forests. This indicator therefore includes a range of other designations of importance. A detailed description of all source data is provided in the following subsections.

To produce the Biodiversity Risk Filter indicator, the raw data was processed as follows: 1) assessment units (terrestrial and marine) were found which overlap with any of the areas detailed in the following subsections, and 2) each assessment unit was classified into the five risk-score classes, following the classification as in the table below.

Biodiversity Risk Filter risk score	Based on other important areas overlapping with terrestrial assessment units
1 - Very low risk	No overlap
2 - Low risk	
3 - Moderate risk	Overlap with WWF Global 200
4 - High risk	
5 - Very high risk	Overlap with intact forest landscapes

Biodiversity Risk Filter risk score	based on other important areas overlapping with marine assessment units (FAO, MEOW)
1 - Very low risk	No overlap
2 - Low risk	
3 - Moderate risk	Overlap with WWF Global 200 or Ecologically or Biologically Significant Marine Areas
4 - High risk	
5 - Very high risk	Overlap with vulnerable marine ecosystems

6.3.1 – Intact Forest Landscapes

An intact forest landscape (IFL) is a seamless mosaic of forest and naturally treeless ecosystems within the zone of current forest extent, which exhibits no remotely detected signs of human activity or habitat fragmentation and is large enough to maintain all native biological diversity, including viable populations of wide-ranging species. IFLs have high conservation value and are critical for stabilising terrestrial carbon storage, harbouring biodiversity, regulating hydrological regimes and providing other ecosystem functions (Potapov, et al., 2017).

6.3.2 – WWF's Global 200

WWF's Global 200 project analysed global patterns of biodiversity to identify a set of the Earth's terrestrial, freshwater and marine ecoregions that harbour exceptional biodiversity and are representative of its ecosystems.

Each of the Earth's ecoregions was placed within a system of 30 biomes and biogeographic realms to facilitate a representative analysis. Biodiversity features were compared among ecoregions to assess their irreplaceability or distinctiveness. These features included species richness, endemic species, unusual higher taxa, unusual ecological or evolutionary phenomena and the global rarity of habitats.

This process yielded 238 ecoregions – the Global 200 – comprised of 142 terrestrial, 53 freshwater and 43 marine priority ecoregions (Olson & Dinerstein, 2012).

6.3.3 – Ecologically or Biologically Significant Marine Areas

Ecologically or biologically significant marine areas (EBSA) are special areas in the ocean that serve important purposes, including the support of the healthy functioning of oceans and the many services that they provide. They are selected via the Convention on Biological Diversity, based on one or more of the following scientific criteria: uniqueness or rarity; special importance for life history stages of species; importance for threatened, endangered or declining species and/or habitats; vulnerability, fragility, sensitivity or slow recovery; biological productivity; biological diversity; and naturalness (CBD, 2021).

6.3.4 – Vulnerable Marine Ecosystems

Vulnerable marine ecosystems (VMEs) are areas within the deep sea that are characterised by their high biodiversity as well as by their high vulnerability to disturbances and that have been delineated following the FAO's International Guidelines for the Management of Deep-sea Fisheries in the High Seas (FAO, 2009). Examples include seamounts, hydrothermal vents, cold water corals and sponge fields.

6.4 – Ecosystem Condition

Reputational risk is likely to be higher in scapes that are still intact or connected, etc., as the impact of corporate activities will be more significant, and of higher profile, as the social/cultural response and critique will be greater. This indicator aims to evaluate intactness and connectivity of ecosystems as a proxy for ecosystem condition, independent of any legal or administrative delineation. As ecosystem condition was already evaluated for indicator 2.4, the same data and risk levels were applied here. However, while in 2.4 low physical risk was associated with intact and connected ecosystems, here high reputational risk is associated with intact and connected ecosystems. Thus the inverse of the 2.4 indicator has been used here.

6.5 – Range Rarity

Reputation risk will likely be highest where corporate actions cause or contribute significantly to a species extinction. Range-size rarity is a measure of species endemism – a state of a species being found in a single and/or restricted geographic range. This indicator specifies those areas where impact on a species might more easily cause or contribute to an extinction.

It is calculated from the area of the pixel divided by the area of the range for each species, i.e. the proportion of the species' range contained within the given pixel. These values are summed across all species to show the aggregate importance of each pixel to the species occurring there (IUCN , 2022).

For this indicator, permission was given to utilise the IUCN Red List of Threatened Species data in the BRF by the IBAT partners (IBAT, 2022).

To produce the Biodiversity Risk Filter indicator, the raw data was processed as follows: 1) the raster data was aggregated data to the assessment units using the max value; 2) it was then classified into the five risk-score classes, following the classification as in the tables below.

Biodiversity Risk Filter risk score	Max range rarity score per assessment unit
1 - Very low risk	<=0,00005
2 - Low risk	<=0,0002
3 - Moderate risk	<=0,0005
4 - High risk	<=0,0008
5 - Very high risk	>0,0008

7 – Socioeconomic Factors

Reputational risk can be driven by negative impacts on local socioeconomic conditions and the local prevalence of socioeconomic issues. This risk category within the BRF comprises the risk indicators: 1) Indigenous Peoples (IPs); Local Communities (LCs) Lands and Territories, 2) Resource Scarcity: Food - Water - Air, 3) Labor/Human Rights and 4) Financial Inequality.

7.1 – Indigenous Peoples (IPs); Local Communities (LCs) Lands and Territories

Whilst global data on IPs and LCs lands and territories exists, this indicator has not yet been included in the map visualisation and the risk assessment. Potential inclusion of this data will be explored with IPs and LCs a priority for the next phase.

7.2 – Resource Scarcity: Food - Water - Air

Sometimes named 'the Big Three', air, water and food are essential for human survival. This trifecta of indicators was included in the BRF to measure where the most basic conditions were at risk, which can compromise working conditions and could potentially reflect badly on companies operating in regions where these conditions might not be met.

To produce the Biodiversity Risk Filter indicator, the highest risk score of the following three raw data sets was used.

7.2.1 – Food Security

The FAO publishes statistics on the prevalence of moderate or severe food insecurity in the total population on a country-by-country basis (FAO, 2021), which has been used as a basis for this indicator. Please note that the source data for this indicator is only available on a country level.

To produce the Biodiversity Risk Filter indicator, the raw data was processed as follows: 1) the country data was aggregated to the HydroBASINS level 7 using the mean value 2) it was then classified into the five risk-score classes, following the classification as in the table below.

Biodiversity Risk Filter risk score	Percentage of moderate or severe food insecurity in the total population
1 - Very low risk	<=8.9
2 - Low risk	>8.9-19.7
3 - Moderate risk	>19.7-37.4
4 - High risk	>37.4-57.7
5 - Very high risk	>57.7

7.2.2 – Water Scarcity

Please see indicator 1.1.1 – Water Scarcity

7.2.3 – Air Condition

Please see indicator 2.3 – Air condition

7.3 – Labor/Human Rights

Labour and human rights are at the basis of just working conditions for employees and the treatment of local stakeholders. The objective of labour and human rights risk management is to prevent, mitigate or end negative impacts of business activity on people (Global Compact Network Germany, 2021). This indicator aims to give a first insight into regional discrepancies in labour and human rights situations.
To create this indicator, the average of the scores for the following two metrics was created.

7.3.1 – Ratified International Human Rights Instruments

As part of their Human Rights Indicators Guide, the UN Human Rights Office of the High Commissioner developed a database of the number of international human rights instruments ratified per country (UN Human Rights Office of the High Commissioner , 2012). This has been used as the basis of this indicator. Please note that the source data for this indicator is only available on a country level.

To produce the Biodiversity Risk Filter indicator, the raw data was processed as follows: 1) the country data was aggregated to the HydroBASINS level 7; 2) it was then classified into the five risk-score classes, following the classification as in the table below.

Biodiversity Risk Filter risk score	Number of international human rights instruments ratified
1 - Very low risk	<=18
2 - Low risk	<=16
3 - Moderate risk	<=13
4 - High risk	<=11
5 - Very high risk	<=8

7.3.2 – Labor Rights Violations

The International Trade Union Congress (ITUC) Global Rights Index depicts the world's worst countries for workers by rating countries on a scale from 1 to 5+ on their degree of respect for workers' rights. Violations are recorded each year from April to March. Detailed information exposing violations of workers' rights in each country is published in the ITUC Survey, found at survey.ituc-csi.org (ITUC, 2020). This has been used as the basis of this indicator. Please note that the source data for this indicator is only available on a country level.

To produce the Biodiversity Risk Filter indicator, the raw data was processed as follows: 1) the country data was aggregated to the HydroBASINS level 7; 2) it was then classified into the five risk-score classes, following the classification as in the table below.

Biodiversity Risk Filter risk score	ITUC Global Rights Index
1 - Very low risk	1
2 - Low risk	2
3 - Moderate risk	3
4 - High risk	4
5 - Very high risk	5 and 5+

7.4 – Financial Inequality

7.4.1 – Financial Inequality

For companies, systemic financial inequality is a great source of risk. It threatens operations and has the potential to destabilise supply chains, trigger political instability and jeopardise their social licence to operate (KPMG, 2022).

The Gini index is a measure of financial inequality and is the basis of this BRF indicator. It measures the extent to which the distribution of income (or, in some cases, consumption expenditure) among individuals or households within an economy deviates from a perfectly equal distribution. A Lorenz curve plots the cumulative percentages of total income received against the cumulative number of recipients, starting with the poorest individual or household. The Gini index measures the area between the Lorenz curve and a hypothetical line of absolute equality, expressed as a percentage of the maximum area under the line. Thus, a Gini index of 0 represents perfect equality, while an index of 100 implies perfect inequality (World Bank, 2021). Please note that the source data for this indicator is only available on a country level.

To produce the Biodiversity Risk Filter indicator, the raw data was processed as follows: 1) the country data was aggregated to the HydroBASINS level 7; 2) it was then classified into the five risk-score classes, following the classification as in the table below.

Biodiversity Risk Filter risk score	Gini Index
1 – Very low risk	<30.8
2 – Low risk	>30.8-36.1
3 – Moderate risk	>36.1-41.6
4 – High risk	>41.6-49.8
5 – Very high risk	>49.8

8 – Additional Reputational Factors

Reputational risk can be driven by the actual or perceived importance or value of ecological assets and socioeconomic conditions and the level of public scrutiny of companies operating in a given geography. Additional reputational factors within the BRF comprises the risk sub-categories: 1) media scrutiny, 2) political situation, 3) sites of international interest; and 4) risk preparation.

8.1 – Media Scrutiny

Media scrutiny indicates whether there has been documented negative news (e.g., incidents, criticism or controversies) related to environmental and social issues that can affect a company's reputational risk. To create this indicator, the higher of the scores for the following two metrics was used.

8.1.1 – Media Scrutiny (Ecological Topics)

For this indicator, RepRisk's (2021) country-specific, weighted score of negative news for all ecological tags was used. Please note that the source data for this indicator is only available on a country level.
To produce the Biodiversity Risk Filter indicator, the raw data was processed as follows: 1) For each country, the number of incidents related to ecological topics were multiplied by their severity score; 2) the country's weighted score was transposed to the HydroBASINS level 7 using the majority value; 3) it was then classified into the five risk-score classes, following the classification as in the table below.

Biodiversity Risk Filter risk score	Sum of incidents*severity per country
1 - Very low risk	0
2 - Low risk	>0-100
3 - Moderate risk	>100-250
4 - High risk	>250-750
5 - Very high risk	>750

8.1.2 – Media Scrutiny (Social Topics)

For this indicator, RepRisk's (2021) country-specific, weighted score of negative news for all social tags was used. Please note that the source data for this indicator is only available on a country level.
To produce the Biodiversity Risk Filter indicator, the raw data was processed as follows: 1) For each country, the number of incidents related to social topics was multiplied by their severity score; 2) the country's weighted score was transposed to the HydroBASINS level 7 using the majority value; 3) it was then classified into the five risk-score classes, following the classification as in the table below.

Biodiversity Risk Filter risk score	Sum of incidents*severity per country
1 - Very low risk	0
2 - Low risk	>0-100
3 - Moderate risk	>100-250
4 - High risk	>250-750
5 - Very high risk	>750

8.2 – Political Situation

Unstable and ineffective institutions and governance can potentially undermine business viability and increase potential for reputational risks.

This indicator is informed by four datasets: violence against land and environmental defenders; the Freedom in the World index; the World Bank's Governance index (The World Bank, 2022); and the Corruption Perceptions index.

8.2.1 – Violence Against Land and Environmental Defenders

For this indicator, Global Witness's record of total number of killings per country was used (Global Witness, 2019). Please note that the source data for this indicator is only available on a country level.
To produce the Biodiversity Risk Filter indicator, the raw data was processed as follows: 1) The country's percentile rank was aggregated to the HydroBASINS level 7 using the majority value; 2) it was then classified into the five risk-score classes, following the classification as in the table below.

Biodiversity Risk Filter risk score	Total number of killings per country
1 - Very low risk	0
2 - Low risk	
3 - Moderate risk	
4 - High risk	1-5
5 - Very high risk	>5

8.2.2 – Freedom

This risk indicator is based on the latest data from Freedom House: the Freedom in the World 2021 (Freedom House, 2021), an annual global report on political rights and civil liberties, composed of numerical ratings and descriptive texts for each country and a select group of territories. The 2021 edition involved more than 125 analysts and nearly 40 advisers with global, regional and issue-based expertise to cover developments in 195 countries and 15 territories from 1 January to 31 December 2020. Please note that the source data for this indicator is only available on a country level.

This indicator has already been calculated in the Water Risk Filter and has been integrated into the Biodiversity Risk Filter without changes. For more information, please consult the Water Risk Filter Methodology or visit the Water Risk Filter directly.

8.2.3 – Governance

For this indicator, the World Bank's worldwide 'government effectiveness in percentile' governance indicator (World Bank, 2010) was used. Government effectiveness captures perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies. Percentile rank indicates the country's rank among all countries covered by the aggregate indicator, with 0 corresponding to the lowest rank and 100 to the highest. Percentile ranks have been adjusted to correct for changes over time in the composition of the countries covered by the indicator.[34] Please note that the source data for this indicator is only available on a country level.

To produce the Biodiversity Risk Filter indicator, the raw data was processed as follows: 1) The country's percentile rank was aggregated to the HydroBASINS level 7 using the majority value; 2) it was then classified into the five risk-score classes, following the classification as in the table below.

Biodiversity Risk Filter risk score	Government effectiveness – percentile rank
1 - Very low risk	>80-100
2 - Low risk	>60-80
3 - Moderate risk	>40-60
4 - High risk	>20-40
5 - Very high risk	>0-20

8.2.4 – Corruption

This risk indicator is based on the latest data from Transparency International: The Corruption Perceptions Index 2020 (Transparency International, 2021). This index aggregates data from different sources that tracks perceptions of business and country experts on the level of corruption in the public sector.

This indicator has already been calculated in the Water Risk Filter and has been integrated into the Biodiversity Risk Filter without changes. For more information, please consult the Water Risk Filter Methodology or visit the Water Risk Filter directly.

8.3 – Sites of International Interest

The sites of international interest comprise RAMSAR and World Heritage sites. Wetlands are among the most diverse and productive ecosystems. They provide essential services and supply all our fresh water. RAMSAR sites highlight important wetlands and encourage their wise use (Ramsar, 2020).[35] World Heritage sites are a collection of unique and diverse places that encourage nature conservation and the preservation of cultural properties (UNESCO-WHC, 2022).[36] Both RAMSAR and World Heritage sites are adopted by intergovernmental processes (the RAMSAR Convention and the World Heritage Convention). To give both RAMSAR and World Heritage sites additional weight, they are considered both as part of the protected areas indicator, and as a unique indicator in their own right.

34 See *https://databank.worldbank.org/source/worldwide-governance-indicators#*

35 See *https://www.ramsar.org/*

36 See *https://whc.unesco.org/*

8.3.1 – World Heritage and RAMSAR sites

For this indicator, UNEP-WCMC's World Database of Protected Areas (WDPA) (UNEP-WCMC and IUCN, 2021a) was used. It is the most authoritative global source of data on protected areas and features Natural World Heritage Sites and RAMSAR sites in its collection.

We were generously given permission to utilise the WDPA data in the BRF by the Integrated Biodiversity Assessment Tool (IBAT) partners (IBAT, 2022).

To produce the Biodiversity Risk Filter indicator, the raw data was processed as follows: 1) Assessment units (terrestrial and marine) were found which overlap with World Heritage Sites, RAMSAR sites, or both; 2) each assessment unit was classified into the five risk-score classes, following the classification as in the table below.

Biodiversity Risk Filter risk score	Based on overlap of natural world heritage sites and RAMSAR sites with assessment units
1 - Very low risk	No overlap with either RAMSAR or natural world hertiage site
2 - Low risk	x
3 - Moderate risk	x
4 - High risk	x
5 - Very high risk	Overlap with either RAMSAR or natural world heritage site, or both

8.4 – Risk Preparation

The level of risk preparation has implications for the kind of coping response needed to the realisation of biodiversity risks which, in turn, can contribute to vicious or virtuous circles in risk management. When effective preparation limits the damages from adverse shocks, coping can be minimal, leaving more resources available for further investments in risk management, reducing vulnerability to future shocks and so on (World Bank, 2014).

8.4.1 – Index of Risk Preparation

For this indicator, the World Bank's Index of Risk Preparation was used (World Bank, 2014). Preparation for risk at the country level includes actions by and contributions from all social and economic groups and institutions, including the state. The index, developed for the World Development Report 2014, comprises measures of assets and services across four important categories – human capital, physical and financial assets, social support and state support – that influence preparation for risk (World Bank, 2014). Please note that the source data for this indicator is only available on a country level.

To produce the Biodiversity Risk Filter indicator, the raw data was processed as follows: 1) The country's percentile rank was aggregated to the HydroBASINS level 7 using the majority value; 2) it was then classified into the five risk-score classes, following the classification as in the table below.

Biodiversity Risk Filter risk score	Index of Risk Preparation
1 - Very low risk	1 (most prepared quintile)
2 - Low risk	2
3 - Moderate risk	3
4 - High risk	4
5 - Very high risk	5 (least prepared quintile)

APPENDIX STEP 1: COLLECTING LOCATION-SPECIFIC COMPANY AND SUPPLY CHAIN DATA

APPENDIX GUIDANCE A: OVERVIEW OF DATA PROVIDERS

1. ASSET-LEVEL DATA

Below is a non-exhaustive list of different asset-level data sets.

Open-source data sets

- **Spatial Finance Initiative:** The *Geoasset databases* of the Spatial Finance Initiative provide information on global cement, iron and steel production assets. The Spatial Finance Initiative is also working on databases covering aluminium, petrochemicals, pulp and paper, waste management and beef production.
- **World Resources Institute (WRI):** The WRI's *Global Power Plant database* provides information on thermal plants (e.g., coal, gas, oil, nuclear, biomass, waste and geothermal) and renewables (e.g., hydro, wind and solar). Each power plant is geolocated and entries contain information on plant capacity, generation, ownership and fuel type.
- **Global Tailings Portal:** Grid-Arenal's free, searchable *Global Tailings Storage Facilities* database contains detailed information on more than 1,800 mine tailings dams around the world, based on mining companies' disclosure.
- **Boston University Global Development Policy Centre:** The BU Global Development Policy Centre's *China's Global Power (CGP) database* provides information on power plants outside China financed by Chinese foreign direct investment (FDI) and/or China's two policy banks.
- **Global Energy Monitor (GEM):** GEM catalogues global fossil fuel and renewables projects in databases and provides trackers covering coal-fired power, fossil infrastructure, coal mines, gas plants, nuclear power and renewables (solar, wind, hydro, geothermal and bioenergy).
- **Leadership Group for Industry Transition:** Its *Green Steel Tracker* collates public announcements of low-carbon investments in the steel industry at asset level. A *Green Cement Technology Tracker* will be available soon.
- **WikiRate:** WikiRate is an open, collaborative platform to answer questions about corporate impacts. The *Fashion Checker: Factories Data* is the result of the Clean Clothes Campaign project to investigate wages in apparel supply chains. The data set covers mostly social aspects but also contains information on the factories' province and city.

Table 10 presents the availability of open-source asset-level data by WWF Risk filter industry classif.

Commercial data sets

Commercial data sets produced by third-party providers are widely available.

- **Asset Resolution** combines sectoral data from individual providers and provides them in a ready-to-use format
- **Four Twenty Seven,** now part of Moody's, is a good source of climate risk data.
- **S&P Global** provides industry specific asset-level covering energy, financial institutions, fintech, maritime and trade, metals and mining, real estate, telecommunications, retail as well as construction.
- The report by the **2 degrees investing initiative** (2017) contains an excellent overview of climate-related asset-level data.

Regulatory data sets

In theory, regulatory data sets can be a great source of information as they mandate disclosure via regulation. In practice, the data is sometimes difficult to extract.

- **EU Emissions Trading System** (*EU Transaction Log*): the EU ETS covers plants producing around 40 per cent of the EU's greenhouse gas emissions and is updated annually. Extracting the data is relatively cumbersome. The private website euets.info processes the data and makes it available.
- **US EPA Greenhouse Gas Reporting Program** (Data sets): the GHGRP contains facility-level GHG emissions data from large emitting facilities in the USA (incl. information on location of sites).

2. CORPORATE STRUCTURE DATA

Below is a non-exhaustive list of data sets illustrating company hierarchies:

- ***FactSet*** *(Data Management Solutions)*
- ***Bloomberg*** *(Global Corporate Structure Data)*
- ***Refinitiv*** *(Ownership, Insiders and Institutional Profile)*
- ***ORBIS*** *(Corporate Structures and Hierarchies)*.

3. COMPARISON OF COVERAGE

Based on FactSet data, we checked the availability of data points linked to disaggregated revenue data (FactSet Georev) for the universe of approximately 60,000 publicly listed companies and compared it with the coverage of corporate structure data (FactSet Data Management solution). Table 9 shows that leveraging disaggregated revenue data would be available for around 30,000 publicly listed companies. Corporate structure data yields information on almost 50,000 companies.

Table 9: Comparing coverage (corporate structure data vs. disaggregated revenue data); Source: FactSet

Industry Sector	Frequency (in sample)		Data on corporate structure and subsidiaries		Data on sectoral and geographical revenue distribution	
(following NACE)	**#**	***% (sample percentage)***	**#**	**%**	**#**	**%**
A - Agriculture and forestry	915	1.51	623	1.26	451	1.42
B - Mining and quarrying	4,366	7.2	3,636	7.36	1,229	3.86
C - Manufacturing	23,179	38.22	16,901	34.21	11,338	35.6
D - Electricity	1,292	2.13	847	1.71	747	2.35
E - Water	396	0.65	330	0.67	209	0.66
F - Construction	1,756	2.9	1,320	2.67	1,054	3.31
G - Wholesale, repair of vehicles	3,900	6.43	3,766	7.62	2,432	7.64
H - Transportation and storage	1,474	2.43	1,094	2.21	881	2.77
I - Accommodation and food service	915	1.51	786	1.59	654	2.05
J - Information and communications	6,191	10.21	5,463	11.06	3,533	11.09
K - Financial and insurance	8,495	14.01	7,713	15.61	4,442	13.95
L - Real estate	3,093	5.1	2,206	4.47	2,290	7.19
Other[1]	4672	7.7	4,713	9.54	2,584	8.11
	60,644	100	**49,398**	100	**31,844**	100

Interpretation: There are around 60,000 publicly listed companies, 915 of them belong to NACE industry sector A (agriculture, forestry, fisheries). For around 600 of them, data on the corporate structure (i.e. the ultimate parent company and its subsidiaries, including location data) is available. For around 450 of them, we have at least disaggregated revenue reporting.

1) 'Other' comprises the NACE macro sectors M-U (covering administration, research and entertainment, amongst others).

Table 10: Open-source asset-level data by WWF Risk Filter industry sector

	Agriculture (animal products)	Agriculture (plant products)	Appliances	Automotives and machinery	Chemicals and other materials	Construction materials	Electric energy (combustion)	Electric energy (hydro)	Electric energy (solar, wind)	Electronics and semiconductors	Fishing and aquaculture	Food and beverage production	Food retailing	General or specialty retailing	Health care, pharmaceuticals	Hospitality services	Land development and construction	Metals and mining	Offices and professional services	Oil, gas and consumable fuels	Paper and forest Product Production	Telecommunication services	Textiles, apparel and luxury goods Prod.	Transportation services	Water utilities and water services providers
Spatial Finance Initiative																									
Cement																		x							
Steel																		x							
Iron																		x							
Aluminium (Planned)																		(P)							
Petrochemicals (P)					(P)																				
Pulp and paper (P)																					(P)				
Waste management (P)																									(P)
Beef production (P)	(P)																								
World Resources Institute																									
Thermal plants							x																		
Renewables								x	x																
Global Energy Monitor																									
Coal (plants, terminals, projects)																									
Steel																		x							
Oil and gas																				x					
Energy							x	x	x																
Others																									
Global Tailings																		x							
China's Global Power Database							x	x	x																
Green Steel Tracker																		x							
Fashion Checker: Factories Data																							x		
EU – ETS				x			x	x	x									x						x	

Table 11: Commercial asset-level data by WWF Risk Filter industry sector

	Agriculture (animal products)	Agriculture (plant products)	Appliances	Automotives & Machinery	Chemicals & Other Materials	Construction Materials	Electric Energy (Combustion)	Electric Energy (Hydro)	Electric Energy (Solar, Wind)	Electronics & Semiconductors	Fishing and Aquaculture	Food & Beverage Production	Food Retailing	General or Specialty Retailing	Health Care, Pharmaceuticals	Hospitality Services	Land Development & Construction	Metals & Mining	Offices & Professional Services	Oil, Gas & Consumable Fuels	Paper & Forest Product Production	Telecommunication Services	Textiles, Apparel & Luxury Good Prod.	Transportation Services	Water Utilities/ Water Serv. Providers
Asset Resolution				x		x	x	x	x									x		x				x	
Global Data				x		x	x	x	x			x			x		x	x	x	x		x	x	x	
WoodMackenzie Upstream Data Tool							x													x					
Rystad Energy Ucube																				x					
World Steel						x												x							
PlantFacts																		x							
Global Cement Directory						x																			
International Cement Review						x																			
WBCSD GNR						x																			
WardsAuto/AutoForecast				x																					
Marklines				x																					
CAPA Fleets																								x	
FlightsGlobal																								x	
Rightship GHG Rating																								x	
shippingefficiency.org BetterFleet																								x	
Clarkson																								x	
Enerdata							x	x	x																
BNEF	x	x		x	x	x	x	x	x									x		x				x	

APPENDIX GUIDANCE A: COMPARING DIFFERENT DATA PROXIES

Table 12: Comparing the four different data sources

	Asset-level data	**Company structure data**	**City of headquarters**	**Disaggregated revenue**
Coverage	Available for a broad range of industries. The largest asset coverage is reached by commercial providers. However, availability of open-source data is limited. See Appendix Guidance A: Overview of data providers, for a more comprehensive overview.	Having checked FactSet data, this data can be retrieved for almost 50,000 publicly listed companies (from a universe of around 60,000). However, the number of retrieved sites per company varies a lot (for 5,457 companies we retrieved more than 10 sites, but for around 45,000 companies, fewer than 10).	Data points that are available in (all) commercial data sets. The coordinates of the headquarters can be used to run the assessment. This data is available for millions of listed and non-listed companies across the globe.	Broad coverage, in particular for publicly listed companies. FactSet, for example, provides this information for around 30,000 companies (see Table 9).
Advantages	- Focus on corporate production facilities (which have the highest biodiversity relevance compared to, for example, real estate or office buildings). - Important attributes available.	- Available in a well-structured format, including industry classifications and company identifiers, which allows for smooth integration. - Regarding coverage, Bloomberg, FactSet and other data providers provide this data for a broad universe of companies.	Data points on the location of headquarters are, in principle, available from any third-party data provider. Also used and tested by the European Central Bank to explore physical climate-related risks of banks.	Broadly available and low implementation costs. Disaggregated revenue by industry sector and by country, combined with the homogeneity assumption, has been frequently applied.
Disadvantages	- (Open-source) data sets can provide a false sense of completeness (since the number of sites per company can differ between commercial and open-source data sets). - Commercial data sets are costly. - Incorporation can be time consuming if company identifiers (such as ISIN or LEI) are missing. (For example: The LEI (Legal Entity Identifier) is missing for 50 per cent of the cases in SFI's cement and steel database.) - Available only for selected industries.	- Relevance of the sites is not entirely clear since many subsidiaries are not associated with the company's main business line. -Since the data product focuses on the corporate hierarchy, production plants might not be part of it when they do not belong to a separate legal entity (e.g., a subsidiary). - Missing location (e.g., coordinates) and industry classification values require a work-around (described in the step-by-step guidance) or to drop observations.	It can provide a false sense of completeness if a company has in fact several physical assets spread across the globe. The accuracy of this proxy relies on the assumption that most production is linked to the headquarter (putting aside the supply chain).	- The spatial granularity is only at the country level which makes it difficult to accurately incorporate the importance and local integrity of biodiversity indicators into the analysis. - The precise revenue distribution per industry and country is not known and analysts must assume that revenue is homogenously distributed across industries and countries. - Revenue is a questionable proxy for physical assets in a country.
Assessment	Recommended to use whenever available due to georeferenced, contextualised site-level data. (First, asset-level data focuses on biodiversity-relevant production facilities. Second, the important contextual attributes facilitate a bottom-up risk measurement.)	This proxy is a great starting point due to broad company coverage and low implementation costs. When using it, analysts should be aware of its limitations. Since the data product focuses on the corporate hierarchy, production plants might not be part of it when they do not belong to a separate legal entity (e.g., a subsidiary).	Only a backup option. Even though this proxy has been used by the ECB to run a risk assessment on millions of portfolio companies, the accuracy of the proxy relies on the assumption that 100% of the corporate production is linked to its headquarter.	Only a backup option due to severe limitations (see cell above) However, due to low implementation costs, this approach may suffice as a first screening tool.

APPENDIX GUIDANCE A: CASE STUDY – THE IMPORTANCE OF INPUT DATA

Asset-level data vs corporate structure data

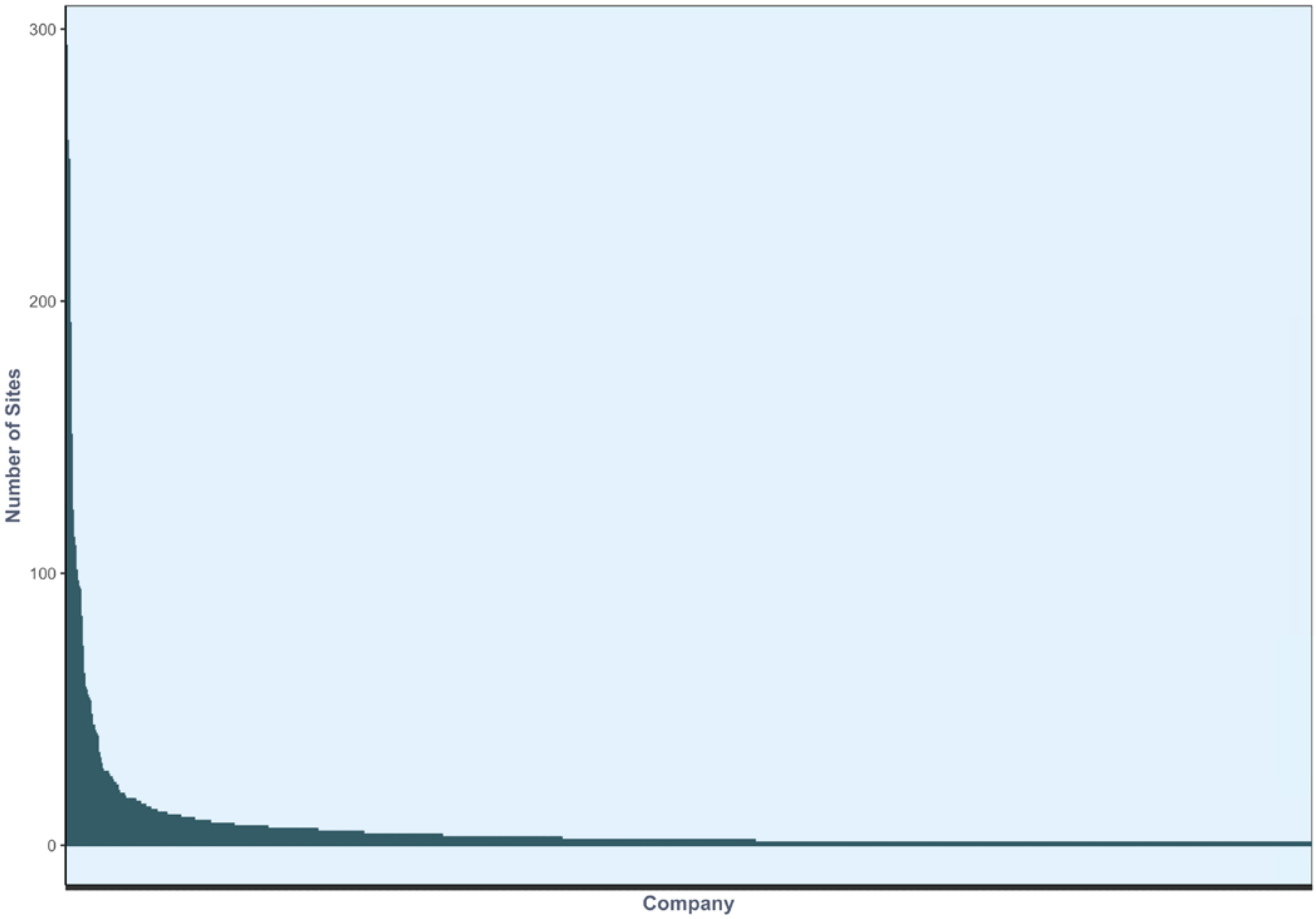
As seen in Table 12, there are different data sources that can be used to build a comprehensive location-specific database. While asset-level data stands out due to its contextualised attributes, corporate structure data can offer a promising solution due to its broad and accessible coverage. To investigate if the contextualised attributes of asset-level data provide additional insight regarding companies' biodiversity risk, we have used the WWF BRF tool to analyse a collection of cement companies using asset-level data (from the SFI database) and corporate-level data (from FactSet).

Although corporate hierarchy data benefits from its broad scale (the FactSet database has around 50,000 data points, see Table 12) the number of sites per company varies widely. Figure 14 below shows the lobsided distribution of the top 1,000 companies in terms of number of sites.[37]

This distribution is partly because of a small concentration of very large global companies, but it also reflects the possible poor data quality that does not register all companies' locations.

If all of a company's sites are not represented in a biodiversity risk analysis, it is likely that risk might not be adequately represented. Could asset-level data lend more accuracy to a biodiversity risk analysis?

Figure 14: Top 1000 FactSet companies by number of sites.



37 The distribution does not reflect the raw data from FactSet's database but is already the result of some data cleaning, as suggested by the workarounds presented in Box 3. Downloading data from FactSet's Data Management Solutions sometimes yields lists of several hundred locations for bigger companies. However, the quality of the location and sector information varies. We delete subsidiaries for which only the country is known and use a spatial extrapolation approach for subsidiaries with location information at city level. As for the sectoral information, some subsidiaries are linked to industry classifications that are different to the company's main business model (for example, some 20 per cent of the subsidiaries of a big cement company are linked to financial services). In a second step, we keep only subsidiaries with a industry classification that is linked to the official corporate revenue reporting.

To explore how the results can change, we compared a sample of 122 companies from the cement industry for which we 1) collected location data from SFI's cement data set; and 2) retrieved location-specific company data from FactSet's Data Management Solutions.

Description of the sample

- SFI cement data set: global distribution of 122 companies across 1,339 locations (see Figure 15)
- Cement companies from FactSet's Data Management Solutions: global distribution of 122 companies across 1,130 locations

Despite the SFI data set containing the company with the highest number of sites (Holcim Ltd, with 193), the average number of sites for both data sets is very similar, at 10 sites per company (see Table 13). Additionally, the mean difference per company between the number of company sites was only 0.05, indicating that the composition of the two data sets is fairly similar.

Figure 15: Overview of company sites identified by the SFI Cement database

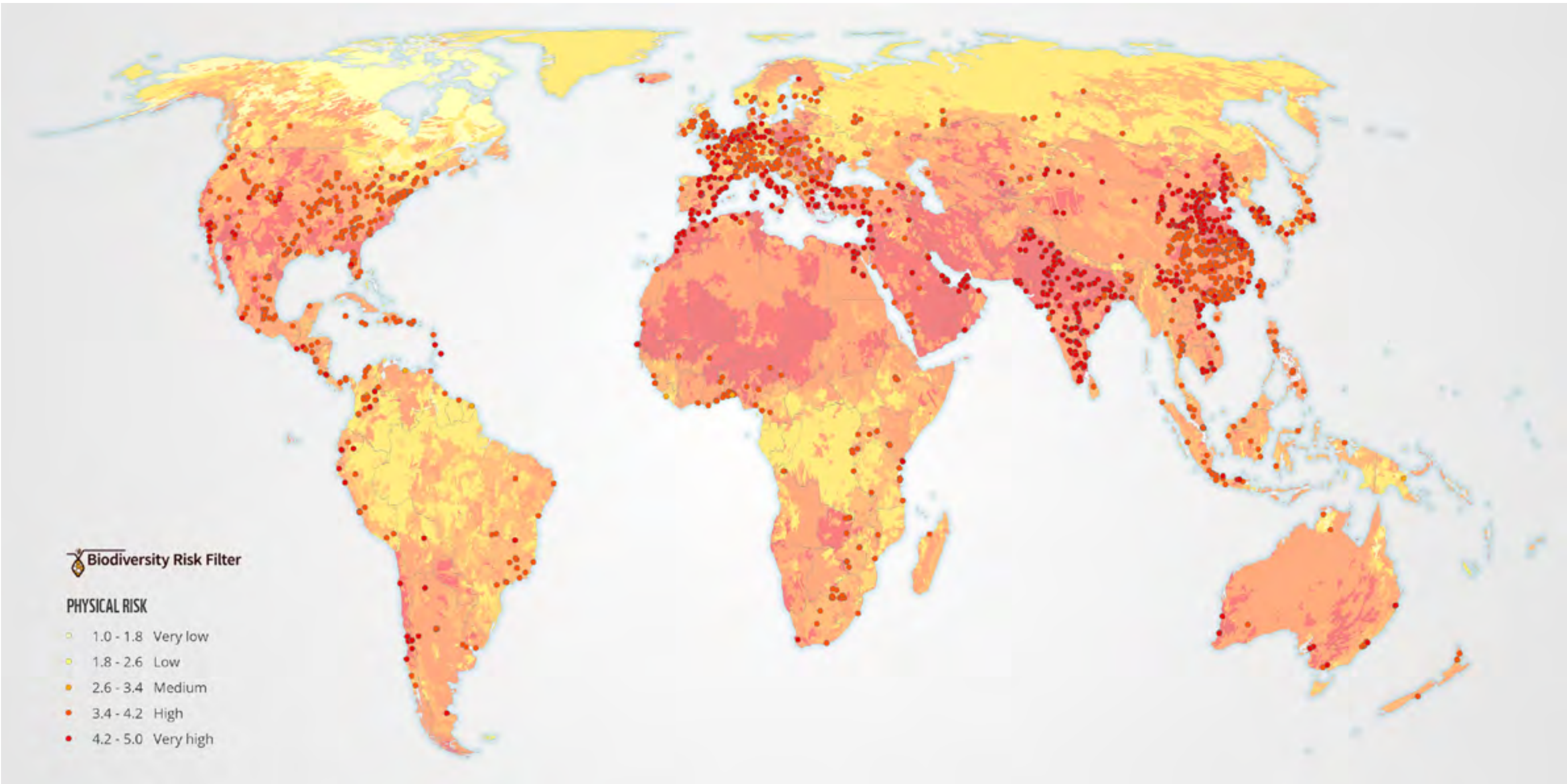


Table 13: Top 10 number of sites from the FactSet and SFI cement data set

Company Name	SFI	FactSet	Difference
Holcim Ltd	193	121	72
HeidelbergCement AG	138	130	8
Anhui Conch Cement Co., Ltd	104	52	52
CEMEX SAB de CV	61	41	20
CRH Plc	58	128	-70
Huaxin Cement Co., Ltd	53	20	33
Buzzi Unicem SpA	42	16	26
China Tianrui Group Cement Co., Ltd	30	6	24
Grupo Argos SA	23	24	-1
Vicat SA	21	21	0
...	...	...	...
TPI Polene Public Co. Ltd	1	2	-1
Mean	9.9	10	-0.05

For the case study, we analysed both SFI and FactSet cement data sets separately, using the November 2022 version of the WWF BRF tool.[38] Following the methodology stated above the scape risk was aggregated to the site level using binning and the 75th percentile method (see Step 2). Site-level risk was further aggregated to company-level risk by weighing each location based on its business importance (see Step 3a).

The results of the analysis show that using asset-level data (the SFI data set) results in slightly higher risk scores on average compared with using corporate-level data. A breakdown of the physical and reputational risk score distribution in Table 14 shows that, while the risk scores of both data sets mostly lie within the 3.0 to 4.0 range, the SFI data set has a higher risk on average. Additionally, a higher percentage of the data set's market capitalisation is exposed to higher risk using the SFI's data set. A possible explanation is that the SFI focuses on corporate production facilities which have a higher risk profile than the administrative operating facilities that are more prevalent in company structure data (which results in slightly different industry sector classifications and hence different industry materiality ratings).

Table 14: Physical and reputational risk score distribution for the SFI and FactSet databases, including % total cement portfolio in market cap.

Score	Physical risk				Reputational risk			
	SFI		FactSet		SFI		FactSet	
	% of companies	% of data set market cap	% of companies	% of portfolio market cap	% of companies	% of data set market cap	% of companies	% of portfolio market cap
0.0 – 3.0	0	0	0	0	0	0	0	0
3.1 – 3.4	12.5	17.2	25	41.4	36.4	60	54	92
3.5 – 3.9	87.5	82.8	75	58.6	54.54	36	37	4
4.0 – 5.0	0	0	0	0	9.1	4	9	4

Despite the table above, on a company-by-company analysis there is an insignificant difference between the use of the two data sets. Figure 16 and Figure 17 show a comparison of the physical risk scores from both the FactSet and SFI data sets. Although some variation exists, the vast majorities have a similar level of risk under both data sets. As shown in Table 13, each company had a similar number of sites and, as such, each company would have a similar amount of detail for each analysis. We can observe that the number of sites is particularly important to the risk analysis. The top 50 riskiest companies in the data sets are presented in Figure 16, in which we see consistent divergence between the risk produced by each data set at the top end. This seems to be driven by a difference in locational data, as the number of sites per company for these companies (top 30) differs between data sets (see Table 13). This result is unsurprising, given that the industry classification for both data sets is similar.[39] As scape risk is an equal combination of the importance and local integrity of biodiversity and industry materiality (see Step 3), given similar industry classifications, much of the difference in risk is explained by locational attributes. A difference in the number of site locations between data sets will then likely have a noticeable effect on risk result. However, we observe a convergence of risk between the two data sets for those companies with a similar number of sites. This might be an indication that corporate-level data could act as a reasonable proxy for asset-level data when the latter is either not available or the fiduciary resources are not present. As more SFI data becomes available, we will repeat the exercise to validate whether the results presented above remain consistent.

38 The case study is based on WWF BRF data from November 2022. As the underlying data is continuously improved, changes may occur that are not reflected in the case study.

39 All companies in the SFI data set are given the industry classification of "Construction Materials" and, although there is more heterogenous industry classification in the FactSet data set, 78 per cent of companies are still classified as being in that industry sector.

Figure 16: Top 50 highest physical risk scores from FactSet and the SFI cement databases

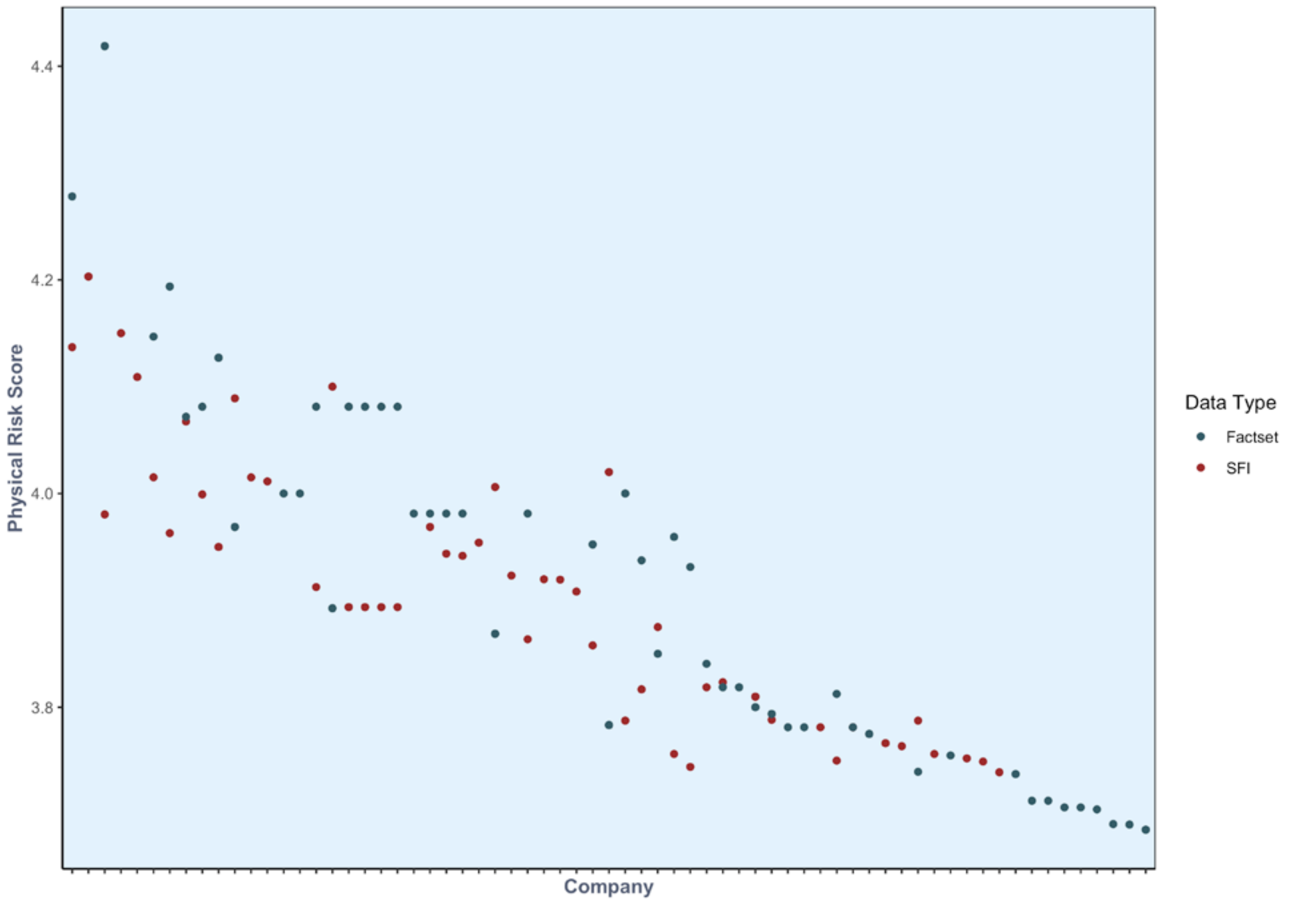
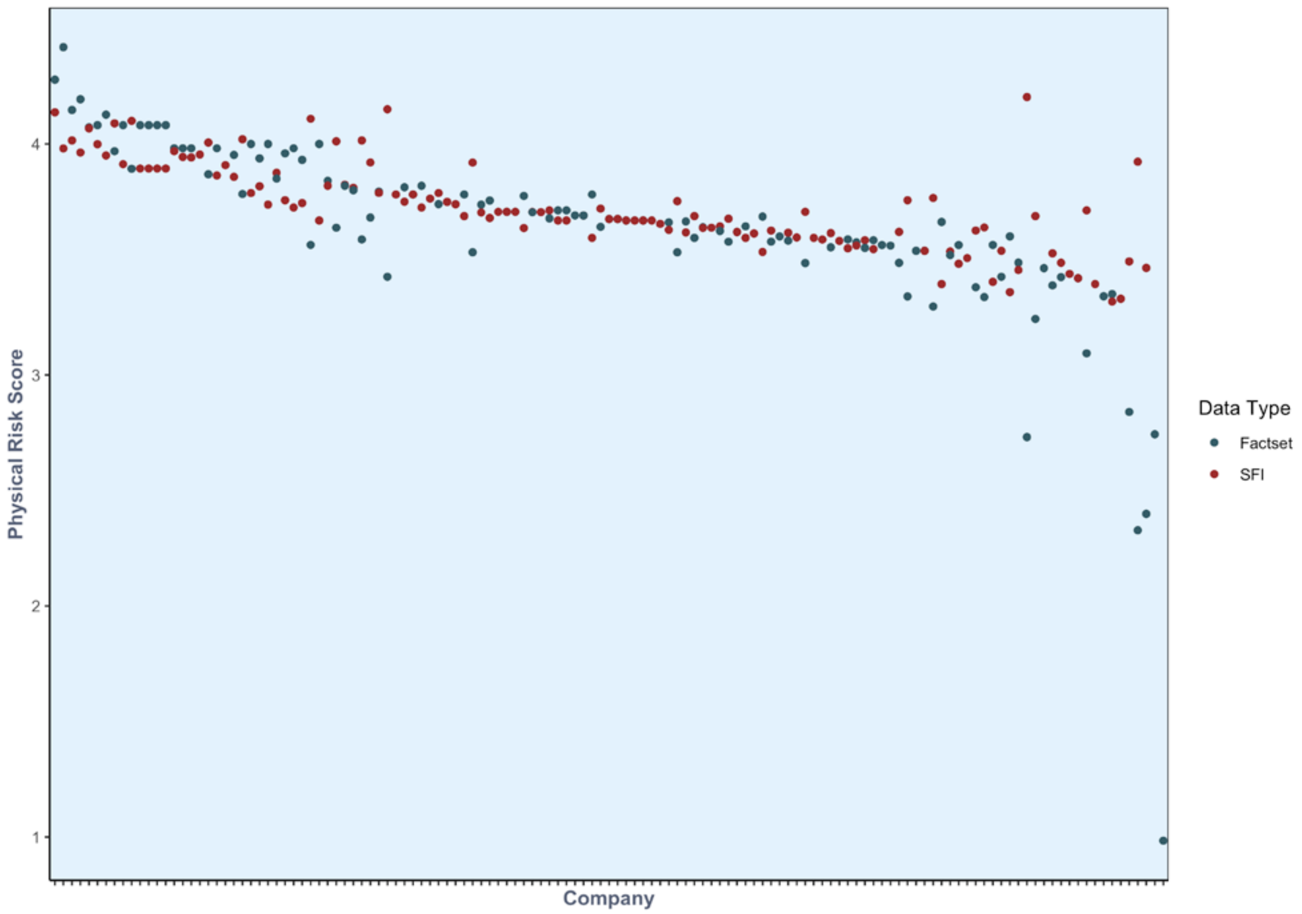


Figure 17: Physical risk scores from FactSet and the SFI cement



APPENDIX GUIDANCE B: OVERVIEW OF IO MODELS

As outlined in our methodology, input-output (IO) models provide a pragmatic and frequently used work-around. This raises the question of which IO model should be used. At least one comparative study has been performed between different *state-of-the-art IO models*, which found that the carbon footprint for most major economies disagree by less than 10 per cent between the most used MRIOs. A detailed discussion on inherent IO model assumptions and limitations is beyond the scope of this paper, but we refer the interested reader to any standard text on the issue.[40]

Furthermore, Table 15 provides a non-exhaustive overview of existing IO models. The decision which IO model to use should depend on the following parameters:

- **Available time series data:** to incorporate relatively up-to-date data into the analysis, the data should not be outdated;
- **Coverage of countries and regions:** some IO models group countries into different blocks, for example 'Rest of the World', which limits usability;
- **Industry sector classification used,** as the industry classification has to be mapped to industry materiality ratings that might be linked to another industry sector taxonomy. For example, if a user wants to merge EXIOBASE with ENCORE, they first have to map the EXIOBASE industry classification to ENCORE's taxonomy of production processes.

Practical considerations on applying IO models

In practice, the user receives a large N_{sector} x $N_{countries}$ matrix from the IO table per country-sector pair, which is mapped to $N_{risk\ indicators}$ (using the BRF industry materiality, for example). Practically, this computation takes a long time when done for a large number of firms on the fly. However, since there is a limited total number of permutations, subject to the number of distinct country-sector pairs of the financial portfolio, the user can pre-compute the upstream risk score for each specific (sector, region) pair to each biodiversity importance or integrity indicator (see Table 8 for the full list of indicators). When doing a computation for any particular company, the user then simply has to compute a weighted average over the relevant (sector, region, biodiversity indicator) triplets.

40 See, for example, Miernyk, (W.H, 1965). *The Elements of Input-Output Analysis*. Reprint. Edited by Randall Jackson. *WVU Research Repository*, 2020, for a good introductory text. Also the (Value Balancing Alliance, 2021), contains an *excellent introduction* including basic descriptions as well as a comprehensive overview.

Table 15: Overview of IO models

Name	Countries or regions	Industries and products	Time series	Satellite accounts	Licensing	Other comments and use cases
GLORIA - Global Resource Input-Output Assessment	164 countries	97 industry sectors	1990-2020	GHG emissions, materials, energy, air pollution, land use, water use, biodiversity, skills and employment	US$20,000 for commercial use	Used, for example, for the Sustainable Consumption and Production Hotspots Analysis Tool (SCP-HAT) (*link*) Technical documentation *here*
EXIOBASE (*link*)	44 countries (28 EU, 16 major economies) and five RoW regions	200 products in 163 industry sector	1995 to 2011, with predictions for more recent years	Resources, emissions, waste flows, packaging, materials and crop residues	Requires permission for commercial use	Used, for example, by Banque de France (*link*)
OECD Global Inter-Country IO (ICIO) Tables (*link*)	66 countries (all OECD countries, all G20, all EU, all ASEAN), 17 region groups, RoW	45 industry sectors (ISIC Revision 4)	1995-2018	Value added and taxes, demand-based material flows	Data can be downloaded for free in zipped *.csv* and *.R data* formats (*here* or *here*)	ICIO provides decompositions of aggregate, bilateral and sectoral exports and imports according to the source and destination of their value-added content
Eora Global Supply Chain Database (*link*)	189 countries	EORA 26: 26 industry sectors Full EORA: 15,909[41]	1990-2015	GHG emissions, labour inputs, air pollution, energy use, water requirements, land occupation, N and P emissions, primary inputs to agriculture from FAOSTAT and Human Appropriation of Net Primary Productivity	*Commercial licence starts from US$10,000 link*	There are two versions of EORA. - Full Eora - EORA 26: a simplified model in a harmonised 26-sector classification. Technical documentation *here*
World Input-Output Database (WIOD) *link*	43 countries (28 EU countries and 15 other major countries)	56 industry sectors and 59 products	2000-2014	Socio-economic: Capital and labour (HS, MS, LS) in physical inputs and factor incomes Environmental accounts (emissions, energy use and resource use)	Available for free in Excel format (*link*)	Applications - Socioeconomic analysis (factor content of trade, effects of outsourcing on labour markets, trade in value added, etc.) - Environmental analysis - Modelling (CGE modelling, dynamic IO-based modelling)
SEI's Input-Output Trade Analysis Tool (IOTA) (*link*)	236 regions	150 agricultural commodities 57 industry sectors	2005-2017	Various resource inputs or environmental extensions, including land area; water (green, blue and grey water), carbon dioxide emissions and nitrogen use	Freely available for use (*link*)	SEI's IOTA model is an environmental footprinting tool that links physical data on commodity production in different countries with a detailed financial matrix that traces inter-industry buying and selling across the world.
Global Trade Analysis Project (GTAP) (*link*)	121 countries and 20 aggregated regions (*link*)	65 industry sectors (*link*)	2004, 2007, 2011 and 2014	Food, resources and manufactures, services	The model can be downloaded from here (*link*)	The most agriculturally-based MRIO in the world, which makes it also highly relevant for a biodiversity-focused assessment. Technical documentation *here*.

41 Preserving sectoral classifications from each data provider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APPENDIX STEP 2: ASSESSING BIODIVERSITY-RELATED RISKS

Percentile

Table 16: Illustrating aggregation using percentiles

Aggregated scape risk per indicator in risk category

	Indicator 1	Indicator 2	Indicator 3	Indicator 4	Indicator 5	75th Percentile
Company A	1	1	1	4	5	4.5
Company B	3	4	2	3	3	3.5

Description: Percentiles as a measure takes the value of the n^{th} percentage number in the distribution.[42] In the case of biodiversity risk analysis, this measure would take the n^{th} percentage observation of all scape risk indicators. A suggested starting point would be the 75^{th} percentile, although any percentile is applicable, given sufficient observations.

Advantages: Using the 75^{th} percentile emphasises high-risk scores. As show in Table 16, this method has the property of emphasising the right tail of risk distributions (higher risks). Although the mean (50^{th} percentile) of indicators for company A (a mean of 2.2) is lower than that of company B (a mean of 3), the high levels of indicators 4 and 5 are emphasised. This method helps to inform companies that certain sites might be highly exposed to biodiversity-related risks that could be integral to business operations. This is important, because even a single issue could result in considerable damage to a business and/or its value chain. The omission of a high-risk score should therefore be avoided.

Disadvantages: There are two disadvantages to the method.

- First, it does not consider the full range of risks, and the scope of its effectiveness remains arbitrary in the percentile chosen. Despite having a higher mean risk across all indicators, company B has a lower risk under the 75^{th} percentile measure than company A. Not incorporating the full distribution of risk into the aggregation measure equals information loss.
- Secondly, how effective the percentile method is at picking up outlier risks is arbitrary to the number given to the percentile. If the analysis in Table 16 had been increased to include ten indicators with the additional indicators having a risk value of 1, then the 75^{th} percentile measure would be 1 and hence would not incorporate the tail risks.

42 For example, the 75th percentile of a distribution with eight observations would be the value of the sixth observation.

APPENDIX STEP 3: A REVIEW OF AGGREGATION METHODS

Several methods can be used to aggregate risks across biodiversity indicators, sites, companies and portfolios, subject to the different level 2 and level 1 risk categories (see Figure 4). Each method has advantages and disadvantages across different dimensions and consideration should be given to various factors, including the statistical literacy of the audience, information loss and feasibility of implementation. If a measure of aggregation is not interpretable, then the severity of risk posed to an asset or company could be underestimated and result in inadequate action. When presenting examples of the different methods, we aggregate across risk indicators per site; however, the methods are applicable to all dimensions

Table 17: Summarising different aggregation methods

	Description	Pros	Cons
Mean	Mean across scape risk indicators.	Broadly understood.	Distribution of risks is not captured. An increased number of observations will reduce the prominence of outliers and diminish the importance of tail risks. This could lead to the understatement of biodiversity risk (which makes it difficult to convey that addressing biodiversity is of importance).
Median	Captures 50 per cent of the distribution.	Robust to outlier values.	Robustness to outliers is also a disadvantage, as the distribution of risks is not captured. Using many different indicators, the final score will be drawn towards the median, which makes it extremely hard to convey that addressing biodiversity is of importance.
Percentile	The nth percentage observation of risk indicators.	Robust to outlier values. High percentile values help to emphasise fat right-tail risks that can be critical to a company or site's function.	Determining the nth percentage is arbitrary. Loss of information as (1-n) per cent of observations are lost.
Moments	In particular, standard deviation and skewness.	Allows for the full visualisation of the risk distribution, giving the analyst a precise understanding of the risk present.	Cannot be presented as a single indicator. Requires statistical literary.

Mean

Table 18: Illustrating aggregation via the mean

	Aggregated scape risk per indicator in risk category				
	Indicator 1	**Indicator 2**	**Indicator 3**	**Indicator 4**	**Mean**
Company A	1	5	1	5	3
Company B	3	3	3	3	3

Description: The mean method provides the simplest aggregation measure and is derived by taking the mean across risk indicators within one aggregation cluster (for example, by taking the mean of all indicators under the level 2 risk category provisioning services, and then taking the mean of all risk categories to the level 1 risk type).

Advantages: The mean (or normalised sum) is broadly understood and interpretable.

Disadvantages: Despite being easily understood, considerable information about the distribution and nature of risks to a company can be lost. As shown in Table 18, two companies can have the same mean risk, although company A is considerably more exposed to biodiversity risk through indicators 2 and 3. This cancelling of risk exposure in the mean calculation is especially pertinent to biodiversity risk analysis, as some indicators work in opposition to one another (e.g., drought and flood risk).

Median

Table 19: Illustrating aggregation via the median

	Aggregated scape risk per indicator in risk category				
	Indicator 1	**Indicator 2**	**Indicator 3**	**Indicator 4**	**Median**
Company A	1	1	1	5	1
Company B	2	2	2	1	2

Description: The median also serves as a simple measure by which to quantify the aggregate scape risk indicators. The N/2th number represents 50 percent of the distribution and it is equivalent to the mean under a typical normal distribution.

Advantages: The median is robust to outlier values. Unlike the mean, the median is not heavily influenced by outlier values that might be an anomaly within the distribution of values.

Disadvantages: That the median is robust to outlier values can also work as a disadvantage in risk analysis as it does not incorporate skewness and fat tails that could pose high levels of risk to a company. In Table 19, we can see that company A has a median lower than that of company B despite being considerably more exposed to indicator 4. Abnormally high levels of risk that could be dangerous if left addressed are not picked up in the median.

Moments

Description: Rather than solely using the first moment (mean) of a distribution of measurements, this method emphasises the use of the first four moments (mean, standard deviation, skew and kurtosis), to provide a description of the aggregation. The addition of a probability distribution could help statistically limited users visualise what the moments convey.

Advantages: By providing more information, this method helps users understand the details of the distribution of scape risks of a company or site. Because each additional moment describes the distribution of risk, it allows the user to infer the importance of the risk to their own application themselves.

Disadvantages: Statistical literacy is required. Furthermore, more than one figure is presented (for example mean and standard deviation) which increases complexity and defies the initial purpose of creating a single score.

Benchmarking explained

Description: Benchmarking is the process by which a company or asset is compared against a group of companies or an index. The comparison allows for a measure of over- or underperformance. To establish a benchmark, a group of companies must first be analysed and all their risks aggregated, which poses its own complications. An example of this would be to compute the risk for all companies in the MSCI World index (following a certain aggregation method) and use this as the benchmark value for biodiversity risk.

Advantages: The method is extremely intuitive and is common practice across the financial world. Because of this, it can be easily understood by all levels of analyst and allows users to understand how a company is operating relative to the market average. Additionally, the inclusion of different benchmarks (sector and region specific) can help analysts understand different landscapes in increased detail.

Disadvantages: The method in essence extends the problem of aggregation, as to benchmark one must first determine a method of company-specific risk aggregation and then a method of aggregating group risks. Additionally, in terms of biodiversity and scape risk, large quantities of data are required to establish a benchmark, as they usually comprise hundreds or thousands of large-scale companies.

APPENDIX 4: LIST OF EXPERTS AND EXTERNAL CONTRIBUTORS

Table 20: List of consulted experts on the Biodiversity Risk Filte

Name	Affiliation	Area of expertise
Alexis Morgan	WWF Germany	Freshwater biodiversity/Water Risk Filter
Alison Midgley	WWF UK	Agriculture and food
Anastasiya Timoshyna	Traffic	Sustainable trade
Ariane Laporte-Biscuit	WWF Germany	Freshwater biodiversity/Water Risk Filter
Axel Krumsiek	WWF Germany	Oceans
Brent Loken	WWF International	Food
Camilla Välimaa	WWF Sweden	Sustainability and business
Carly Cowell	KEW	Invasive species
Carolina Soto-Navarro	UNEP-WCMC, WWF Vietnam	Multidimensional Biodiversity Index
Chris Weber	WWF	Climate and energy
Christine Scholl	WWF Germany	Agriculture
Colman O'Criodain	WWF International	Invasive species
Craig Beatty	WWF US	Forests and GIS
Daniel Brizuela	WWF US	GIS, supply chain risk analysis
Daniel Metzke	PIK	Planetary boundaries
David J. Patterson	WWF UK	Conservation Intelligence/WWF SIGHT
David Olson	WWF Hong Kong	Ecosystem type metrics
Deon Nel	WWF Netherlands	Conservation
Elaine Geyer-Allely	WWF International	Governance
Elisa Vacherand	WWF International	Sustainable finance
Florian Titze	WWF Germany	Governance and regulation
Franck Hollander	WWF Germany	Oceans
François Gardin	Polygones E.R.I., advisor WWF DK	Oceans, investment, risk analysis
Ghislaine Llewelynn	WWF International	Oceans
Gregory Gigoi	BCG	Data analysis
Guido Broekhoven	WWF International	Policy and regulation
Isabel Meza	WWF Germany	Risk analysis/Water Risk Filter
Jaco Du Toit	WWF Sweden	Biodiversity and policy
Karen Luz	WWF International	Food
Karen Mo	WWF US	Forests
Karin Bilo	WWF Germany	Oceans
Kathy Hughes	WWF UK	Freshwater biodiversity

Name	Affiliation	Area of expertise
Laura Prill	WWF Germany	Forests
Lin Li	WWF International	Policy and regulation
Luca Chinotti	WWF International	Policy and regulation
Margaret Kinnaird	WWF International	Invasive species
Maja-Catrin Riecher	WWF Germany	Agriculture
Malou van Kempen	WWF Netherlands	Oceans
Margareta Renström	WWF Sweden	Business and biodiversity
Mario Vaupel	BCG	Risk hierarchy
Mark Heuer	WWF Germany	Oceans
Martha Stevenson	WWF US	Forests
Matthew Wilkinson	WWF International	Corporate transformation and sustainability
Melissa de Kock	WWF Norway	Climate models
Michele Thieme	WWF US	Freshwater biodiversity
Nicolas Poolen	WWF Netherlands	Green finance
Pablo Pacheco Balanza	WWF US	Forests and GIS
Philip Leonard	WWF International	Freshwater biodiversity
Philipp Kanstinger	WWF Germany	Oceans
Philipp Wagnitz	WWF Germany	Ecosystems and natural resources
Pierre-Yves Hardy	WWF France	Oceans
Rafael Camargo	WWF Germany	Water Risk Filter
Sandeep Chamling	WWF International	Climate models
Shaun Martin	WWF US	Climate models
Stefano Esposito	WWF Norway	Agriculture and food
Susanne Schmidt	WWF UK	Agriculture and food, WWF SIGHT
Tanja Draeger de Teran	WWF Germany	Agriculture
Vanessa Pérez	WWF International	Climate models
Vishaish Uppal	WWF India	Governance and regulation
Wendy Elliot	WWF International	Wildlife conservation
Review by relevant groups:		
WWF Global Science +		
Biodiversity Stewardship Governance Committee		
Business Advisory Group		
IBAT Scientific Committee		

Table 21: WWF Switzerland External Advisory Group and Investor Group

Name	Organization
Anne Schoenauer	2° Investing Initiative
Benjamin Gränicher	Consultant
Chiara Colesanti Senni	Council on Economic Policies
Christoph Biehl	Credit Suisse Asset Management
Corli Pretorius	UNEP-WCMC
Doris Hauser	Forma Futura
Farah Nadiah Fadzil	Khazanah Nasional Berhad
Gautier Desme	S&P Global
Grant Rudgley	Cambridge Institute for Sustainability Leadership (CISL)
Harriet Wildgoose	Fidelity
Jakub Červenka	2° Investing Initiative
Jessica Smith	UNEP FI
Judson Berkey	UBS
Karianne Lancee	UBS
Liudmila Strakodonskaya	AXA Investment Management
Mark van Oorschot	PBL Netherlands
Michal Kulak	Robeco
Mieke Siebers	Foundation for Sustainable Development
Naasir Roomanay	Ninety One
Nico Frey	Radicant
Philipp Staudacher	Radicant
Robert-Alexandre Poujade	BNP Paribas Asset Management
Romain Svartzman	Banque de France
Sam Anthony	Ninety One
Sebastian Becker	UNEP-WCMC
Sebastian Wiesel	J. Safra Sarasin
Susanne Schmitt	Consultant
Therese Niklasson	Newton Investment Management
Wendy Francesconi	International Center for Tropical Agriculture (CIAT)

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