Good Data, Good Questions: Leveraging Comprehensive, Direct-Observation Data Sets for Impactful Research on Organizations and the Environment

Good Data, Good Questions: Leveraging Comprehensive, Direct-Observation Datasets for Impactful Research on Organizations and the Environment[1]

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Abstract

Much research on organizations and the natural environment relies on self-reported corporate data of dubious reliability and accuracy. A new wave of data, originating in satellite observations, forensic genetics, hydrological maps and other sources, can help overcome these shortcomings. We identify several datasets from the natural sciences that are easily accessible and highly accurate, and provide roadmaps for management researchers to utilize them. We further explore the types of research questions these datasets enable, extending beyond the confines of environmental-financial performance relationships that have dominated previous research. By leveraging these and similar datasets, corporate sustainability researchers can obtain clearer insights into corporate environmental impact, opening doors to new avenues of inquiry.

Keywords: Sustainability datasets; corporate environmental impacts; interdisciplinary research; data quality; research design

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As planetary boundaries are increasingly transgressed (Richardson et al., 2023), the field of organizations and the natural environment (ONE) is called upon to engage more directly with how organizational practices relate to specific, concrete changes in planetary biophysical systems, and especially to investigate the environmental impacts of corporate actions (Boons, 2013, Hahn, et. al., 2024, Russo, et al., 2024; Williams, et al., 2025). Yet, these calls have so far failed to fundamentally reorient ONE research. On the contrary, in recent decades, the focus of ONE research has shifted from environmental impacts to economic performance (Burbano, et al., 2024). Corporate Environmental, Social and Governance (ESG) ratings receive more attention than actual positive or negative effects of organizations on biophysical systems (Schaltegger et al., 2022; Williams et al., 2025). Similarly, in the domain of social and environmental entrepreneurship, only a handful of articles have measured ultimate social and environmental impacts (Johnson & Schaltegger, 2020; Vedula et al., 2022).

Our paper is motivated by a conviction that if we – as ONE researchers – wish to engage meaningfully with organizational environmental impacts , then we need good data, in the form of valid and appropriate constructs (Van de Ven, 2010), that comprehensively capture the effects of organizational practices on local and planetary biophysical systems. Our goals in this paper are therefore threefold: 1) to spotlight datasets that incorporate variables portraying biophysical systems and that are already being harnessed for ONE research; 2), to help ONE scholars in their research endeavors by describing research strategies that make these datasets suitable and relevant for organizational research; and 3) to set forth criteria that can help ONE researchers identify additional datasets originating in the natural sciences that can be utilized for future research.

Exploring the relationship between organizations and biophysical systems

Thirty years ago, Gladwin and colleagues criticized how organization sciences followed a "fractured epistemology […] disassociating human organization from the biosphere" (Gladwin et al., 1995, p.896). Time has passed, planetary boundaries have been transgressed, and yet calls for research to better situate the role of organization within – and not aside from – biophysical systems (Williams et al., 2025), persist.

One barrier to such research is the limited engagement of ONE scholars with variables representing the dynamics of these biophysical systems (Russo et al., 2024). Indeed, recent research has identified critical research questions exploring how organizations depend on or impact biophysical systems and what role they play in supporting their resilience, but addressing these research questions necessitates engagement with new datasets on these biophysical systems (Lahneman et al., 2025). These datasets often present methodological and theoretical challenges for ONE researchers. But they also provide compelling opportunities for innovative research design and fresh perspectives. Our paper strives to show how such datasets can effectively be used by ONE scholars, using a data quality assessment framework (Wang & Strong, 1996) that acknowledges the importance of data users' specific needs.

To date, many quantitative ONE studies assess firms' environmental performance by utilizing ESG datasets that are intended primarily for investors and others in the financial community. The vendors that provide these datasets gather granular information about corporate environmental practices and impacts (Berg et al.,2022; Delmas, et al., 2013). These data points – often numbering in the hundreds for each company – are then aggregated, yielding rankings or scores that purport to represent environmental performance. In short, these datasets are heavily intermediated (Callery & Perkins, 2021), in a manner suited to ESG investing, but not

necessarily suited to other audiences (Cort & Esty, 2020; Eccles et al., 2020; Heath, et al., 2023). The way they are weighted and aggregated (Chatterji & Toffel, 2010; Mattingly & Berman, 2006), in conjunction with their limited scope (Liesen et al., 2015; Lyon et al., 2018; Slager & Gond, 2022), results in partial and imprecise information about the direct impact organizations have on biophysical systems (Boons, 2013).

It is of course undeniable that ONE scholars obtain some benefits from using ESG datasets that are in widespread use. ESG datasets unburden researchers from difficult choices regarding causality, weighting, and validity. As such, they streamline the research process, allowing scholars to circumvent the effort associated with discovering, understanding, preparing and explaining datasets grounded in the natural sciences, domains that are not typically their core area of expertise.

Given this reality, it is not trivial to shift away from using these "tried-and-true" datasets, because researchers face publication requirements and institutional pressures that disincentivize the extra effort required to seek and organize new data (Russo, et al., 2024; Etzion, 2007). Many of the influential studies in our field have examined variations on the "it pays to be green" hypothesis, and, in so doing, have given the ESG datasets that underlie them an imprimatur of approval (Berchicci & King, 2021). Employing these same datasets in subsequent research both reduces the time required to complete a study and, through familiarity, reassures reviewers about data adequacy. Convenience and conformity have thus led to the utilization of datasets that focus on corporate sustainability practices, rather than actual impacts of organizational practices on local and planetary biophysical systems.

Fortunately, barriers to high-quality biophysical data are diminishing (Grégoire et al., 2024). Due primarily to evolving technological capabilities, datasets on a wide variety of

environmental topics are increasingly available for analysis (Etzion & Aragon-Correa, 2016, Nilashi et. al., 2023), and new techniques to provide reliable measures have emerged. These datasets could provide researchers with accurate variables to examine the complex and mostly unexplored relationship between organizational practices and the biophysical conditions of the ecosystems we rely on. They provide an opportunity to "shift … the dependent variables we study to authentic environmental impacts" (Russo, et al., 2024, 127).

Ensuring data quality with alternative datasets

Of course, not all datasets that measure environmental impacts are of sufficient quality and relevance for ONE research. Perhaps the biggest challenge is that datasets commonly used in the natural sciences are not structured around organizational units of analysis, such as company or industry. Accurately attributing a focal company's actions to specific environmental variables is a challenging endeavor. And because such datasets are rarely used in management studies, uncertainty can deter many from engaging with them. Given these hurdles, our overarching objective in this article is to examine whether and how datasets employed by other disciplines can be utilized by ONE researchers.

To methodically set forth the strengths and weaknesses of natural science datasets, we follow a highly regarded framework for assessing data quality set forth by Wang and Strong (1996), and subsequently refined for bigger datasets (Cai and Zhu, 2015; Haug, 2021; Omri et al, 2020). This framework allows for an assessment of data taking into account data users' needs along four dimensions: A*ccessibility, intrinsic quality, contextual relevance, and interpretability*. These are, by design, not entirely objective or universal criteria because, as a general rule, data quality is contextual and subjective (Omri et al, 2020). In other words, a dataset that is suitable for one use-case is not necessarily suitable for other use-cases (Parris and Kates, 2003). Hence,

our descriptions below emphasize the most salient issues for ONE researchers as data consumers:

1. *Accessibility* refers to how easy it is for individual researchers to obtain the data. Is it universally accessible or restricted to paid subscribers? Do researchers face opportunity costs to manage and utilize the data effectively? Moreover, do the dataset owners follow transparent practices, and is replicability possible?
2. *Intrinsic quality* encompasses desirable characteristics of datasets, regardless of their intended use, such as accuracy, objectivity and validity. To assess intrinsic quality, one must ask questions such as: Is the data sufficiently precise? Is it unbiased? Is it timely? Does it truly represent the constructs we seek to study?
3. *Contextual relevance* prompts reflection on whether the data is truly useful to the research project. For ONE research, can the data help test, refine, and expand our theoretical toolkit? Is the scale of the data suited to organizational levels of analysis? Can impacts be attributed to firms, industries, or other organizational entities?
4. *Interpretability* (labeled by Wang & Strong, 1996, as representational quality) refers to the manner of data presentation. Can ONE researchers understand and make sense of the way the data is structured? Are they familiar with the constructs and the units used in the dataset? Is the data aggregated or otherwise constructed in a way that reduces its informational value?

These questions can serve as a checklist for assessing the attractiveness of a novel dataset for research purposes, and can be considered in sequence: first, determine whether access to the dataset is at all feasible; second, explore whether the dataset contains "good" metrics; third,

decide whether it is relevant to the research purpose; and fourth and finally, reflect on whether and how meaning can be constructed from it.

In the following sections, we examine these dimensions of data quality in five datasets that engage with issues of water management, forest conservation and deforestation, ocean salinity, and carbon emissions. Following these assessments, we offer a summary table highlighting typical trade-offs that must be considered when selecting direct-observation datasets for studying organizational impacts on biophysical systems. We also provide a non-exhaustive overview of research questions that could be tackled with the datasets we highlighted, and ones similar to them. We conclude with a brief overview of emerging trends and technological innovations that can provide opportunities for even more pathbreaking research in the future.

Lucie Baudoin: Leveraging Data for Innovative Water Management Studies

Previous research has outlined the scarcity of quantitative empirical work aimed at understanding how organizations address water issues (Baudoin & Arenas, 2020; Kurland & Zell, 2010). Much can and should be done to address this shortcoming, by merging available datasets to develop a systemic understanding of how water systems interact with organizational practices.

A First Approach to Water Data: The Hydrological Setting

Compared to other environmental matters, and especially greenhouse gas emissions, water issues are much more "localized" in terms of their biophysical and social dynamics. Water management needs to be contextualized, and the standard level of analysis in research on water issues is a river basin, or watershed. Hence, a researcher interested in studying corporate water management should be cognizant of the distinct watersheds impacted by organizational activities (at headquarters and other facilities) and their biophysical specifics.[1]

This is a fairly easy first step. Data on basin boundaries worldwide is readily available online (in GIS format) in the HydroBASINS database (Lehner & Grill, 2013). Although it does not contain much information about the biophysical conditions in these basins, it can be used to structure corporate data along meaningful hydrological areas, which often do not match administrative units (as is evident in Figure 1). This dataset is somewhat rudimentary on its own, yet it unlocks important research questions around whether and how the basin(s) in which organizations or individuals are located impact their behavior or level of awareness regarding water issues, echoing for example recent research on organizational attention and scale (Bansal et al., 2018). To explore such questions, researchers can add in river basin affiliation as an independent or control variable in a host of statistical models, from classical regressions to cluster analysis. Yet, although it is easily accessible, recognized as accurate and fairly easy to interpret, HydroBASINS, as a stand-alone dataset, is relevant only for very specific research questions. As we will see below, combining basin boundaries with more local datasets creates more possibilities.

-----Insert Figure 1 about here-----

Another global resource is the World Resources Institute open-access dataset, Aqueduct, which is easily accessible and available under a Creative Common license[2]. The Aqueduct dataset is mostly concerned with water stress and risk at the international level, and has been used to supplement large-scale cross-sectional and panel data to compare national policies (e.g. Jorgenson, 2007; Shandra et al., 2011). But there are gaps in Aqueduct data coverage, and its coarse geographical indicators (Kuzma et al, 2023) lack the level of granularity necessary to establish a relationship with sub-national organizational practices, thereby reducing contextual relevance for many ONE research questions. All told, a researcher looking for a readily available

dataset with global coverage to link organizational practices to issues of water quality or quantity will be left wanting.

Consequently, researchers examining organizational water management must access regional or national datasets, depending on their research needs. The World Bank Water Data[3] website offers an overview of a broad range of datasets on various sub-topics which might be relevant to researchers' needs. Naturally, these datasets may be less familiar to ONE researchers, raising legitimate questions about their quality. As I will show hereafter, the biggest challenges might be around contextual relevance and interpretability, but such challenges can be tackled.

Digging into Specific Datasets

In my own research project, I was concerned with how the biophysical conditions of river basins influenced corporate and NGO participation patterns in collaborative governance (Baudoin, et al. 2023), and in turn, if these participation patterns made any long-term difference in the average water quality of river basins (Baudoin & Gittins, 2021). To that end, I needed longitudinal data depicting water quantity and quality in the basins studied. Such aggregated indicators were not available, as is often the case, but extensive raw data was (on the French Naïades[4] and Hydro[5] databases). These datasets were public, thus accessible, and measurements were mostly accurate, as they were validated by experts in public agencies using precise scientific procedures. A key concern – arguably one that would challenge any social scientist engaging with water data – was that of data interpretability.

Even more so, my main difficulty pertained to contextual relevance, meaning whether the datasets I found could allow me to causally relate environmental conditions to specific organizational practices, and therefore make claims on environmental impacts. At any fixed measurement point in a river basin, many alternative phenomena can explain pollutant

concentration levels or river flow, e.g., dam release policies, precipitation patterns, and soil composition. Control variables that account for key biophysical dynamics of hydrological systems are therefore imperative for isolating the environmental impact of organizational activities.

As I tried to see whether participation patterns in river basin committees made a difference on various water quality parameters, I worked with an environmental scientist familiar with this kind of data. Together, we developed a statistical model to control for seasonal variations of river flows. This allowed us to causally link nitrate pollution to agricultural practices, and to an organizational variable – the presence of agricultural representatives in water governance deliberations. We also needed to factor in the concurrent evolution of anthropogenic pressures on the river basins studied (population density, land use), with the evolution of percentage of artificial land cover (e.g. industry, mining, urban development) in the river basins studied. This data was obtained from the EU-initiated CORINE Land Cover dataset[6]. Working with such data can also spark new research ideas: In our case, geographical data helped situate key actors of collaborative governance within their hydrological setting by providing information about the average land use type within a 10 km radius of their location (see Figure 2).

-----Insert Figure 2 about here-----

Opportunities and Challenges

Despite growing interest in organizational and management studies on water issues, there are currently no plug-and-play datasets available to researchers. However, the situation is likely to improve as better technology, particularly integrated sensors, are adopted more widely, thereby improving intrinsic quality. Intrinsic quality will also increase as governance structures evolve to incorporate environmental monitoring procedures and share their information systems. These

trends will also improve accessibility. Inherently, water data from hydrological sources will be contextually relevant for ONE researchers trying to understand and conceptualize organizations as located within biophysical systems rather than administrative units, such as counties or regions. However, researchers must still overcome the main concern, attributability, which is essential for properly interpreting the data and creating organizational knowledge from it.

To ensure such attributability, one approach is to rely on longitudinal data, which allows researchers to track the parallel evolution of corporate actions and water-related outcomes. For example, if some companies abruptly change a management practice, one could implement a regression discontinuity research design. Proper specification of control variables is also critical, because water issues can only be understood in a biophysical and social context (e.g., water quantity in proportion to population density). An important rule of thumb is to refrain from including only one variable as indicative of water conditions as one could do with tons of CO_2 equivalent in climate studies. Finally, depending on the region studied, the inclusion of control variables representative of the dynamics of the biophysical system will likely limit the geographical or temporal scope of analysis, yet it is crucial for yielding meaningful results. In this process, organizational scientists will benefit greatly from investing time to connect with natural scientists that usually work with these local datasets.

Leandro Pongeluppe : Using Satellite Data to Advance Systemic Management Research on Forests and Oceans Sustainability

Remote sensing data collected using satellites can be a valuable tool for exploring environmental topics and researching how organizations and managers might contribute to sustainable practices and outcomes. This approach has several advantages as regards data quality (Wang and Strong, 1996). First, satellite data provides researchers with objective, measurable

information about actual outputs rather than subjective data based on scores or ratings. Second, data is precise, and its measurement is consistent across time and space, making intertemporal and cross-sectional analysis comparable and informative. Third, most satellite data is easily accessible and available to researchers at no cost. Indeed, some scholars have already used satellite data to evaluate the management practices of specific firms (McGahan & Pongeluppe, 2023; Natividad, 2014) and industries (Kivleniece et al, 2024; Nagaraj, 2022). In this section, I provide two examples: forest conservation and fire occurrences in the Amazon region, and oceanic salinity levels worldwide. The examples illustrate how satellite data is already advancing management research, specifically on the potential ecological impact of firms and industries.

The Amazon Rainforest: Forested Areas and Fire Incidents

Elinor Ostrom, the 2009 Nobel Prize laureate in Economics, together with Harini Nagendra, wrote:

> Satellite remote sensing is the most frequently used technique for mapping changes in forest cover. When combined with on-the-ground observation, studies of land-cover change enable us to analyze social incentives and actions and explore environmental and social change. (Ostrom & Nagendra, 2006, p. 19225)

The Brazilian National Institute for Space Research (INPE) has a repository of datasets on forest conservation/deforestation and fire incidents in the Brazilian Amazon region from 2000 onwards[7]. Both microdata and aggregate data by municipality are openly available to the public, in English. INPE's system uses Landsat-5/TM satellite imagery and traces the yearly evolution of land cover in the Amazon region (Almeida et al., 2016). Moreover, by law, INPE has a mandate to monitor real-time potential harm to the Amazon biome and report instances of deforestation and fire to the Brazilian Federal Police (Souza-Rodrigues, 2019). Therefore, the institute also compiles daily data on the number of fire incidents detected[8]. Figure 3 illustrates this data using Geo-Information Systems (GIS) and its intertemporal evolution.

-----Insert Figure 3 about here-----

Suppose that a group of management researchers are interested in understanding "how and to what extent do firms affect forest conservation efforts in the Amazon?" These researchers may combine INPE's data with geolocated information about private and public activities to assess the degree to which different initiatives and individuals might be fostering forest conservation or depletion. For instance, in recent research, Natura, a cosmetics company famous for its use of Amazonian bioingredients in cosmetic products (Boehe et al., 2014; Gatignon & Capron, 2023), has been shown to positively impact forest conservation after developing supply chain agreements in several Amazonian municipalities (McGahan & Pongeluppe, 2023). Similarly, research has demonstrated that agribusiness leaders (i.e., mayors with agribusiness backgrounds) do not deforest the Amazon significantly more than their non-agribusiness counterparts (Cordeiro et al., 2023).

Both research projects used quasi-experimental techniques to estimate the impacts of these initiatives on forest outcomes. This is possible if researchers use the spatial distributions of these variables and associate them with the locations that firms affect. By merging data geographically, researchers can analyze cross-sectional and intertemporal variations in ecological outcomes and have a more systemic understanding of management effects on forests. In other words, to the extent that researchers can geolocate the activities of firms, they can merge these with the panel data structure of forest outcomes provided by INPE, and estimate the degree to which these activities contributed or hindered forest conservation in the Amazon. Research of this nature helps to validate programs and management practices that either promote forest regeneration or reduce forest depletion. Moreover, it helps to debunk myths about individual backgrounds and leadership styles that would be detrimental to conservation efforts.

Since these datasets allow researchers to assess the effect size of private and public interventions in total forest area and/or number of fires, it is possible to roughly calculate and estimate the ecological effect of forest preservation in terms of Carbon tons (Ct) stored or biodiversity preserved, among other indicators. This is possible, since the literature has detailed information on how many tons of carbon are stored and how many species exist on average per hectare in the Amazon (Souza-Rodrigues, 2019; McGahan & Pongeluppe, 2023). Furthermore, these datasets can be complemented with information on agricultural production to evaluate potential synergies and/or trade-offs between forest preservation and agricultural frontier advancement.

Inevitably, remote sensing forest data has limitations. INPE's satellite system, for instance, detects only clear-cut areas larger than 20–30 meters (Kintisch, 2007, p. 537), leaving smaller disturbances and selective timber logging undetected. Moreover, forest coverage does not necessarily equate to ecosystem health, as it overlooks vegetation quality, biodiversity gradient, and ecological resilience. For example, forested areas may be monocultures of commercial species such as açaí or rubber trees, which are less ecologically robust than primary forest areas. Therefore, as noted by Ostrom and Nagendra (2006) in the opening quote of this section, researchers should complement satellite information with on-site observations whenever possible.

Salinity Levels of Oceans

Ocean salinity data offers management researchers a reliable physical indicator of firms' environmental footprints in marine ecosystems. Changes in salinity can reveal how industrial activities, such as desalination or resource extraction, may be affecting local ocean conditions.

NASA's Aquarius mission uses remote sensing to map oceans' salinity levels, temperatures, and sea ice levels, among other variables[9]. Natural scientists use these data to better understand salt concentration and temperature in ocean waters, and their effect on freshwater cycles and global climate (Cullum et al., 2016; Olson et al., 2022; van Westen et al., 2024). The satellite system has tracked daily variations in the global ocean surface and depth salinity at a resolution of 150 kilometers (93 miles) since 1992.

Moreover, the Aquarius mission developed a collaboration with Argentina's space agency (CONAE), which built complementary sensors to detect rain, sea ice, wind speed, and sea surface temperature. Jointly, this data can be used to study phenomena ranging from natural hazards to land processes, as well as air quality evaluations. As shown in Figure 4, salinity levels vary throughout the year mainly due to the melting of the Arctic Sea ice during summer in the Northern Hemisphere.

-----Insert Figure 4 about here-----

Suppose a group of management researchers wants to understand "how and to what extent is a firm affecting local oceanic ecosystems?" These researchers can geolocate the activities of this firm – or group of firms within the same industry – and evaluate the effect of their operations in comparison to areas where they could be operating but are not. Indeed, management researchers have combined this data with information on the geolocation of water desalination plants to determine the impact of efforts to produce fresh water using sea water on local marine ecosystems (Kivleniece et al., 2024). By merging NASA datasets with the geographical locations of desalination plants (using plants' latitude and longitude), researchers may directly assess the average effect of these plants on local marine environments, as well as understand the effects of: (a) specific firms, (b) their plant ownership structure (i.e. public or

private), and (c) their desalination technology (i.e., thermal or membrane); on ocean health. Kivleniece et al. (2024) show that public and private clients have heterogeneous preferences for technologies when commissioning desalination plants, with some firms using technologies more detrimental to local maritime environments than others. To wit, firms' governance structure directly affects the likelihood of desalination plants discharging brine (a concentrated salty solution, which is a byproduct of the desalination process) back into the ocean. The heterogeneous disposal of brine can damage local marine ecosystems (Gacia et al., 2007), increasing salinity levels and reducing the amount of oxygen in specific coastal areas. Similarly to the forest example, researchers can estimate the effect size of launching desalination plants on local plankton, marine bacteria, and coral bleaching, and can create general equilibrium models of the impacts of increased salinity on currents and ice-cap levels.

Opportunities and Challenges

These two examples provide insights into how remote sensing through satellites can be helpful in further developing management research. In line with Wang and Strong's (1996) framework, datasets for forest conservation, wildfires, ocean salinity, and ocean temperature are fully accessible. The raw datasets are publicly available and have been systematically collected for decades. The data is highly accurate, having been validated by the agencies providing them. Data is also precise. Forest fires and deforestation sites are detected and recorded as long as they affect an area of 30 square meters or greater (Kintisch, 2007).

Perhaps most importantly, the data is contextually relevant. Given its geographical and oceanographical coverage, these datasets can be merged with conventional datasets on organizational and industrial activities using spatial measures such as latitude and longitude. Since these datasets are available over different time periods, it is possible to not only perform

cross-sectional comparisons, but also to identify intertemporal patterns, and even execute quasi-experimental analyses evaluating the impacts of specific individuals, firms and industries on local ecological outcomes and ecosystems.

In this respect, these datasets' main challenge is attribution, i.e., clearly distinguishing between anthropic and natural occurrences, to correctly pin-down the causal path to changes in the dependent variable. Variations in fire incidents, forest depletion, and oceanic salinity and temperature are influenced by the seasonality of natural processes. For instance, we see in Figure 3 and Figure 4 that, depending on the season, there are more or less fire occurrences in the Amazon, and the seawater can be more or less saline. These changes occur partially due to natural processes related to the dry season in the Amazon during the Southern hemisphere winter, and due to melting in the Arctic ice cap during the Northern hemisphere summer, respectively. Therefore, it is essential to perform detailed and well-identified data analyses to pinpoint instances where variations occur due to anthropic actions, which are precisely where management can matter.

Finally, interpretability is adequate. It is not difficult to understand the main variables in the datasets since their measurements are usually standardized in area (km^2 or hectares) and number of occurrences (count) for forest conservation and fire incidents, respectively; or in parts per thousand (‰) or degrees Celsius (ºC) for ocean salinity and temperature, respectively. However, it is imperative that researchers understand the magnitude of systemic effects revealed by their analyses. For instance, how much carbon tons (Ct) are saved or how much biodiversity is preserved is essential to understanding the impact of potential management interventions in forested areas. Similarly, comprehending the effect sizes of one standard deviation increases in

ocean salinity or temperature on local marine ecosystems is fundamental to drive recommendations for managers.

In sum, satellite data in these two biophysical systems is of high intrinsic quality, contextually relevant, accessible, and fairly interpretable as long as researchers investigate the underlying biophysical properties and relationships among the measured outcomes. To this end, researchers need to dedicate effort to understand the datasets and measures, the data-generating processes, and the economic and ecological significance of their results.

Patrick Callery: Carbon Emissions Data Alternatives—Climate TRACE

Research on organizational responses to the climate crisis has flourished in recent years, with a commensurate need for high-quality data on corporate greenhouse gas (GHG) emissions. Many data sources have emerged to meet this need, based on a patchwork of climate disclosure mechanisms (e.g., CDP, formerly the Climate Disclosure Project), standalone company reports, emissions disclosure regulations, and economic modeling, the vast majority of which draw on company self-reported data. Yet, corporate carbon emissions reporting standards are varied and notably flexible (Brander et al., 2018; Depoers et al., 2016), and verification and assurance measures are unreliable at best (Callery & Perkins, 2021; Talbot & Boiral, 2018). Firms have considerable discretion when calculating and reporting company emissions, prompting questions about intrinsic quality.

Fortunately, the emerging availability of big data through government projects, advanced satellite imagery, and other publicly available data sources offers researchers alternative measures that provide a more granular or "bottom-up" assessment of corporate emissions. In this section, I describe the benefits and limitations of one such data repository offered by Climate TRACE, a not-for-profit coalition of organizations formed in 2020 to independently monitor

global sources of greenhouse gas emissions. Climate TRACE uses machine learning to analyze big data available from satellites and remote sensors, combined with other data sources, to estimate direct GHG emissions from individual emissions sources ("assets") worldwide. Existing facility-level datasets suffer from selective availability (e.g., direct corporate reports) or discrete jurisdictional boundaries (e.g., reporting regulations). Climate TRACE overcomes these limitations through direct observation, mitigating a key endogeneity concern associated with datasets derived from self-reported emissions.

Climate TRACE data is easily accessible, made freely available to the public via its website under the Creative Commons Attribution 4.0 International Public License[10]. The data covers 10 emissions-intensive, "hard to decarbonize" sectors: agriculture, buildings, fluorinated gases, fossil fuel extraction and processing, forestry and land use, manufacturing, mining, power generation, transportation, and waste management. Within each sector, separate methodologies (42 total to date) have been developed to capture the unique nature of emissions generation in specific subsectors. For example, within the manufacturing sector, separate methodologies and datasets cover four particularly carbon-intensive subsectors—cement, aluminum, steel, and chemicals, pulp, and paper—as well as a general methodology covering more than 40 smaller subsectors. These emissions methodology reports provide a transparent description of data acquisition, clarifying emissions-related operational matters within the sector being studied. They are also a useful resource for ONE researchers when writing an informed discussion of limitations in a manuscript.

Climate TRACE data is generally comprehensive, covering more than 660 million geo-located assets.[11] Sectors with known point sources (e.g., manufacturing, power generation, oil & gas operations) are reported at the facility level (i.e., a single facility represents one asset)

whereas sectors and subsectors with disperse emissions (e.g., road transportation, agriculture, forestry) are reported at regional aggregations, along with featured example analyses of point sources in different sectors. Perhaps most importantly, Climate TRACE data includes several identifiers to enable merging with other data sets. Specifically, each asset contains a unique Climate TRACE source identifier, along with country and geolocation (latitude and longitude) data points. For most sectors with facility-level data, a separate file is provided that maps individual facilities to parent organizations, allowing for merging with other data sets by organization name, and thereby making the data contextually relevant for ONE researchers.

Illustrative Example: Steel Manufacturing Emissions

I illustrate the utility of Climate TRACE data by means of the following description of the methodology and estimated emissions for the steel manufacturing sector. To estimate emissions from steel manufacturing, Climate TRACE assembled a database of all known global steel facilities from Global Energy Monitor, a non-governmental organization devoted to cataloging information on energy generation and energy-intensive sectors, and Worldsteel, a global trade association for the steel industry. Climate TRACE's steel dataset currently includes monthly emissions estimates from 2021 to 2024 for 894 facilities located in 78 countries.

Steel manufacturing generally employs two main technologies for the most energy-intensive phase of production—blast furnaces (primary processing of iron ore, typically powered by coal or gas combustion) and electric arc furnaces (secondary processing of post-industrial recycled scrap, powered by electricity). Blast furnace facilities produce infrared heat signatures that are readily detectable in satellite images and are collected and analyzed by Climate TRACE to estimate production levels. Figure 5 shows an example of the infrared heat signature for a large blast furnace facility where variation in the thermal profiles over time enables Climate

TRACE to segregate hot spots into different production processes, each with different baseline emissions factors. These in turn are aggregated to provide an assessment of total Scope 1 emissions at the facility.

-----Insert Figure 5 about here-----

Aggregating Emissions to Parent Companies

For many organizational researchers, contextual relevance requires analysis at the individual firm level. In the case of steel plants, Climate TRACE aggregates facility ownership based on Global Energy Monitor data. A drawback is that this ownership data covers only one point in time, so transfers in facility ownership are not captured. Currently, data must be matched by parent company name to other research data sources; however, Climate TRACE offers unique firm identifiers (Legal Entity Identifier, LEI) for some data sets to facilitate matching with other corporate data sets.

Table 1 presents a list of the 10 largest global steel manufacturing parent companies by average production output in 2022. Note that only two of the 10 largest firms report to CDP, which is the basis for many global corporate emissions data products.

-----Insert Table 1 about here-----

Variance in Company-Reported Emissions

Figure 6 compares Climate TRACE's estimated emissions with parent company emissions disclosures submitted to CDP. Whereas the 34 steel manufacturing firms reporting to CDP made a total of 124 annual emissions disclosures during the period from 2015 to 2023, Climate TRACE provides 4248 firm-year observations (aggregated from monthly data) associated with 472 parent companies over the same time period, and is therefore much more comprehensive. The 45° dotted line in Figure 6 corresponds to perfect alignment between the

two data sources, and the dashed line represents a linear fit, suggesting high face validity for the Climate TRACE data. Discrepancies may be due to various confounding factors, e.g., operations in multiple industrial sectors, complex ownership structures or reporting boundaries, discretion in emissions calculation standards, incorrect disclosure, or of course errors in Climate TRACE's methodology.

-----Insert Figure 6 about here-----

Opportunities and Challenges

Representative and accessible data on firm and facility-level GHG emissions are of utmost importance to researchers of climate change and organizations. Climate TRACE provides an unbiased, physical observation-based source that can help address a variety of compelling research questions related to regulatory effects, voluntary initiatives, and corporate disclosure, among others. The data is provided in monthly increments and consistent over time, enabling panel data analysis and event studies. It is easy for management researchers to understand and to access, enhanced by detailed sectoral methodologies and descriptive analyses to aid researchers in interpreting and integrating the data.

However, appropriate caution must be taken when using the data. First, Climate TRACE is specifically a facility (or "asset") level data source—aggregating data to corporate parents introduces uncertainty associated with the varied emissions sources of diversified firms and the accuracy and timeliness of facility-parent company data, which is provided by Climate TRACE only for some sectors in select time periods. Aggregating data to corporate parents over time may thus require independent effort from researchers.

Second, Climate TRACE should not be seen as a cross-check on the accuracy of direct emissions disclosures by firms. In Climate TRACE, emissions are inferred from, for example,

satellite-based infrared heat signatures. As such, the data are only as accurate as the algorithm that translates satellite and other data into emissions estimates. Moreover, the emissions data inferred in some Climate TRACE sectoral methodologies are not directly observed, but rather estimated by integrating direct satellite observations with other data sources. Researchers should acquaint themselves with the technical details of Climate TRACE methodologies for the sectors utilized, making note of any limitations on intrinsic quality or contextual relevance. Moreover, Climate TRACE estimates only direct (Scope 1) emissions from observable assets worldwide. Thus, it does not provide users with a comprehensive view of a company's total emissions footprint, which commonly includes indirect (Scope 2 and 3) emissions. However, as described above, it represents a contextually relevant, objective, publicly available, and comprehensive view of global, asset-level, direct observation-based emissions estimates across a range of carbon-intensive sectors, with regular monthly updates.

Cady Lancaster and Rajat Panwar: Assessing natural resource supply-chain sustainability

Ensuring transparency in opaque supply chains has become a key concern for corporate social responsibility and sustainability scholars (Kim and Davis, 2016; Murcia et al., 2021) and is particularly pronounced in the natural resource sector. Technological advancements, such as Internet of Things (IoT) devices, artificial intelligence, and blockchain, have been touted as potential solutions (e.g., Bai & Sarkis, 2020). However, while these tools are generally effective, they cannot trace origins when transnational criminal networks intentionally commingle contraband with legitimate goods as they flow through supply chains. This can jeopardize even companies with strong sustainability commitments and extensive technological infrastructure.

Consider this situation: In 2020, Earthsight reported that "IKEA, the world's biggest furniture retailer, has for years sold children's furniture made from wood linked to vast illegal

logging in protected forests in Russia. It is one of several Western firms linked to the case" (Earthsight, 2020). Shortly after, IKEA issued the following response: "IKEA does not accept illegally logged wood in our products. The results of the 3rd party investigation … and our own internal investigation … showed no indications that illegally logged wood has entered our supply chain" (IKEA, 2020).

Reconciling such disparate conclusions can be challenging, making the verification of product origins a crucial concern for the forest products sector, where the illegal wood trade has grown into a $52-$157 billion annual criminal enterprise (Kar & Spanjers, 2017). This illicit trade not only drives deforestation, biodiversity loss, and violence (Butt et al., 2019; Panwar et al., 2023), but also causes significant economic losses and harms the reputation of the forest sector in general (Kar & Spanjers, 2017; Gasson et al., 2021; Hansen et al., 2013). To address this challenge, two broad approaches have emerged: (1) macro risk assessment, and (2) taxon and origin tracing. The resulting repositories provide science-based evidence to help researchers, companies, and regulators determine the provenance of timber products.

Macro risk assessment

The risk of illegal wood infiltrating the supply chain can be assessed using aggregate tools and trade network mapping. The Global Illegal Logging and Associated Trade Risk Data Tool (ILAT)[12] is a supply-chain risk assessment tool, aiding in tracking timber and identifying areas with heightened risks of illegal logging. ILAT is based on monitoring the movement of wood products such as lumber, pulp, and paper globally, helping to pinpoint key producers, processors, and trade routes or to compare the trade policies of different countries (see Figure 7). It can be used to analyze governance, corruption levels, and forestry practices across different countries to flag entry points where illegally sourced wood may enter the supply chain (Saunders

& Norman, 2020). ILAT is freely accessible, enabling businesses, researchers, and consumers to make more informed decisions about the wood they purchase.

-----Insert Figure 7 about here-----

While ILAT serves as an aggregate summary tool that enhances trade network transparency based on countries' practices and profiles, a more detailed risk assessment of specific supply chains can be conducted by analyzing transportation and processing practices (Nonato et al., 2025). In the United Kingdom, due diligence guidelines recommend trade network analysis including risk assessments of the country using publicly accessible information including NGO reports, species-specific harvesting risk for vulnerable species, and supply chain tracing[13].

Taxon and origin tracing

As part of supply chain risk assessments, identification or verification of taxon (species information e.g., *Betula pendula*, "Birch") and origin provenance (e.g., *Betula pendula* from a specific forest concession in Latvia) are integral parts of supply chain traceability. However, timber is complex, both as a biological material and as a processed product, and no single analytical method has been developed that wholly resolves traceability questions. Traceability tools for taxon range from analysis of wood anatomy using microscopy or machine learning of images, genetics, and chemistry. Origin tracing tools utilize chemical analyses, stable isotope ratio analysis, trace element analysis, and genetics. While there are many tools, reference databases are disparately accessible.

With respect to identification of timber already on the market, identifying the genus or species of wood by its microscopic anatomical structure is the longest standing and most accessible tool in academic research and supply chain verification (Price et al. 2021), due to a

robust online database. A free, web-based database called InsideWood[14], comprising over 10,000 descriptions of wood with nearly 70,000 images, makes taxon identification accessible (Wheeler 2011). InsideWood integrates standardized wood anatomical features for taxonomic identification (Wheeler et al. 2020). Additional taxonomic resources like Plants of the World Online[15] (POWO) and the Tree of Life Explorer[16] are online repositories of aggregated plant data that provide information on identification, reference images, and introduced and natural distribution. Together, InsideWood, POWO, and the Tree of Life Explorer provide rich resources that can be used to identify and match species with likely geographic origins. Genetics is also a successful tool for identification with accessible reference data from sources like POWO, GenBank, and Tree of Life Explorer. However, extracting intact DNA from wood products for testing purposes is a complex and costly process which has limited the utility of the databases for supply chain traceability. Robust chemical methods for species identification are available – but the databases are closely guarded (Price et al., 2022).

Origin verification remains a difficult element of supply chain traceability. Complementary techniques like stable isotope ratio analysis (SIRA) and trace element analysis (TEA) are being increasingly applied to establish wood origins and improve accuracy (Mortier et al., 2024). High-resolution georeferenced databases in which samples are linked to specific geographic locations using spatial coordinates such as latitude and longitude are being developed globally (Gasson et al., 2021; Ng et al., 2022), but SIRA and TEA databases have yet to become open source in the same way that genetics and anatomy have. As such, no single approach is sufficient; a combination of methods and databases – used both sequentially and in parallel – are necessary to establish product provenance and assess illicit trade in wood products.

Opportunities and Challenges

ONE researchers aspiring to work on supply chain tracing with these datasets face accessibility challenges. In contrast to the datasets described in previous sections, assessing origins and identifying contraband requires physical samples collected and analyzed by skilled professionals, increasing the cost of research. This is likely to render *large-n* studies prohibitive, but does create unique opportunities of working in interdisciplinary teams on more tightly focused research questions about specific corporate actors, sub-sectors or countries of origin. In these cases, sampling can be deliberate, and products can be assiduously linked to specific firms, thereby strengthening causal claims. By contrast, if seeking to work at the level of international business, the ILAT risk data tool can provide useful measures of supply chain risk in the global forest products trade. Moreover, similar approaches can be used in other plant-based sectors like cocoa, soy, and cotton, where supply chains are equally opaque and far-reaching, making product authentication similarly difficult (Savage, 2016). These sectors may be appealing for ONE researchers to focus on in future research.

Discussion

"[T]he historical arc of corporate sustainability research suggests that it is becoming disconnected from pressing environmental issues." (Burbano et al., 2024, 135). We share this concern and propose prescriptions on how it can be remedied: "[S]cholars … need to redirect their attention toward measuring and studying environmental problems" (Burbano et al., 2024, 150). As our overview intimates, we believe that this redirection of attention is not only eminently doable but is in fact underway. Technological advancements across various fields in the natural sciences, from genetics to remote sensing, are enabling management researchers to conduct sound, meaningful, and potentially pathbreaking research. Objective, near-real-time, comprehensive datasets with global coverage are readily available – often at minimal or no cost

(Boose, et al., 2007). We call upon management scholars to engage with these datasets and methodologies seriously, and to learn, understand, and associate them with organizational practices.

A particularly appealing attribute of these datasets is that they support significant and much-needed theoretical development while grounding these developments in biophysical systems properties. The brief overviews in this article illuminated some of these efforts, especially in the domains of water, forest fires, deforestation, ocean salinity, and biodiversity. Complementing Lahneman and colleagues' (2025) examination of new research frontiers around planetary boundaries, Table 2 provides an overview of some research questions that the highlighted databases can help answer. These questions echo timely research endeavors in various ONE research streams, including sustainable supply-chain management, corporate misconduct, and place-based approaches.

-----Insert Table 2 about here-----

These questions and databases are far from exhaustive. Sharma (2022) proposed additional transdisciplinary avenues of inquiry on issues like air pollution, food security, human health, and ways in which organizations can restore and improve ecosystems. Databases on various dimensions of environmental sustainability, such as biodiversity, soil health, or biogeochemical flows (Richardson et al., 2023) are already available and accessible to ONE researchers[17]. In fact, almost by definition, any dataset that academics in the natural sciences have labored to assemble pertains to topics that are important to study from the perspective of organizational impacts on the environment. At minimum, a broader set of metrics for assessing organizational environmental impacts will promote a more holistic understanding of

organizational performance. More enticingly, they may even allow management scholars to construct novel theories of sustainable corporations (Sharma, 2022).

Indeed, the field's central constructs - such as corporate environmental performance, stakeholder salience, and sustainability strategy - have so far been inferred through proxies and perceptions. Integrating comprehensive direct-observation biophysical datasets can transform these constructs from interpretive estimates to empirically grounded measures. This shift will not only enhance validity but will also redefine the kinds of theories the field can build: from those centered on disclosure and intent to those centered on impact and causality.

Taking up this challenge stands to reshape research on organizations and the natural environment in profound ways. Access to high-resolution, longitudinal environmental data enables the testing of theories about organizational adaptation, ecological feedback loops, and system resilience that were previously speculative. Concepts like legitimacy, boundary spanning, or dynamic capabilities can be revisited through an ecological lens, where firms are not only social actors but biophysical agents operating within planetary boundaries. This reconceptualization could re-anchor the field in its founding ambition: To study organizations as part of, not apart from, biophysical systems. Organizations *and* the environment.

Of course, integrating direct-observation datasets with organizational measures is a demanding task, requiring thoughtfulness and effort. As depicted in Table 3, although natural science datasets tend to meet intrinsic quality requirements and provide avenues for accessibility, they still pose challenges to ONE researchers in terms of contextual relevance and interpretability. These hurdles are not insurmountable, as we have described above, and summarize below.

-----Insert Table 3 about here-----

One approach applicable to several of the datasets described above is to track organizational activity and environmental impacts in a given biophysical setting over time. As is the case for longitudinal research designs more broadly, this approach can better specify and assign causality, in particular through the use of quasi-experimental methodological designs. Another approach is to more tightly circumscribe research settings to specific regions or industries characterized by particularly significant environmental impacts that are easier to track and attribute. A third approach, which is likely to become more tractable as new data sources become available, is to aggregate point impacts at the level of a facility (which can be as small as an individual oil or water well) or tract of land (forest or field) up to the parent organization that controls it. This form of data aggregation will be facilitated by increasingly powerful machine learning systems (Nilashi et. al., 2023). Big data and machine learning also create opportunities for predictive modeling and testing and will make it possible for ONE researchers to generate forecasts and scenarios for the future, as is common in other disciplines (cf. Burke, et al., 2015; Otto, et al., 2020).

Although we see much that can be gained through using novel datasets from outside the management and organizational sciences, it is important to emphasize that they too, just like datasets already used for ONE research, can suffer from data quality deficiencies. These range from faulty observations, through inconsistency over time, to poor weighting (Ellison, 2010; Miola and Schiltz, 2019; Pasquier, et al., 2007). We do not propose that alternative datasets are, in and of themselves, a panacea, nor that their quality is assured. We do believe, however, that many of these hazards can be understood and mitigated by seeking advice and information from domain experts, and benefiting from the body of knowledge that has already been produced through the creation and utilization of these datasets. Potentially, such exchanges can also lead to

the refinement and expansion of datasets in ways that enable management researchers to more cleanly tease out causality and determine attribution for positive and negative impacts.

Furthermore, working with databases developed and maintained by domain experts in other fields provides an entry point to interdisciplinary scholarship. Although working with scholars from other disciplines might require overcoming social and institutional barriers (Becher & Trowler, 2008), the very act of communicating and interacting with scholars from other disciplines on tangible problems related to assembling and analyzing data can provide the necessary motivational and cognitive impetus (Lahneman et al., 2025; Kaplan, Milde & Cowan, 2017) that is often lacking in interdisciplinary research projects. “Intellectual reciprocity” (Jasanoff, 2011: 11), enacted through data work can promote the “radical interdisciplinarity” needed to “drive constructive scholarly progress” (Russo, et. al., 2024: 126), and yield high impact publications (Leahey, Beckman, & Stanko, 2017), while also being more relevant for practice (Rau, Goggins, & Fahy, 2018; Shrivastava, Kasuga, & Grant, 2023).

In this sense, the integration of natural science datasets is not merely methodological innovation; it marks an epistemological turn toward materiality. Much as the availability of genomic data redefined biology or climate modeling redefined meteorology, the growing accessibility of planetary-scale environmental data can redefine management research. These datasets allow ONE scholars to evolve from organization-centered to planet-centered analyses, a transition from describing sustainability efforts to empirically tracing how organizational actions alter Earth systems. Closer alignment with planetary science and earth governance research can connect the social and natural sciences in a genuinely integrated framework.

Our field has the capacity to engage more meaningfully with the environmental impact of organizations, through finding and using good data to answer good questions. Doing so, we

believe, will increase the influence and relevance of ONE research. We also believe that the ONE scholarly community can rise to this challenge: bridging disciplinary divides, leveraging diverse expertise, and pioneering new ways to accurately measure the environmental impacts of business activities, and thereby helping mitigate harm. Toward that end, we offer this article not as a conclusion, but as a beginning.

References

Almeida, C. A. de, Coutinho, A. C., Esquerdo, J. C. dalla M., Adami, M., Venturieri, A., Diniz, C. G., Dessay, N., Durieux, L., & Gomes, A. R. (2016). High spatial resolution land use and land cover mapping of the Brazilian legal Amazon in 2008 using Landsat-5/TM and MODIS data. *Acta Amazonica*, *46*(3), 291–302. https://doi.org/10.1590/1809-4392201505504

Bai, C., & Sarkis, J. (2020). A supply chain transparency and sustainability technology appraisal model for blockchain technology. *International Journal of Production Research*, *58*(7), 2142–2162. https://doi.org/10.1080/00207543.2019.1708989

Bansal, P., Kim, A., & Wood, M. O. (2018). Hidden in Plain Sight: The Importance of Scale in Organizations' Attention to Issues. *Academy of Management Review*, 43(2), 217-241. https://doi.org/10.5465/amr.2014.0238

Baudoin, L., & Gittins, J. R. (2021). The ecological outcomes of collaborative governance in large river basins : Who is in the room and does it matter? *Journal of Environmental Management*, 281, 111836. https://doi.org/10.1016/j.jenvman.2020.111836

Baudoin, L., Zakriya, M., Arenas, D., & Walsh, L. (2023). Would You Walk 500 Miles? Place Stewardship in the Collaborative Governance of Social-Ecological Systems. *Journal of Business Ethics*, 184(4), 855-876. https://doi.org/10.1007/s10551-023-05362-8

Becher, T. and Trowler, P. (2008). Academic tribes and territories: Intellectual enquiry and the culture of disciplines. UK: McGraw-Hill Education.

Berchicci, L., & King, A. A. (2021). Building Knowledge by Mapping Model Uncertainty in Six Studies of Social and Financial Performance. *Strategic Management Journal*, *43*, 1319–1346. https://doi.org/10.1002/smj.3374

Berg, F., Kölbel, J. F., & Rigobon, R. (2022). Aggregate Confusion: The Divergence of ESG Ratings. *Review of Finance*, *26*(6), 1315–1344

Boehe, D. M., Pongeluppe, L. S., & Lazzarini, S. G. (2014). Natura and the development of a sustainable supply chain in the Amazon region. In L. Liberman, S. Garcilazo, & E. Stal (Eds.), *Multinationals in Latin America: 49-71. London: Palgrave Macmillan.* (pp. 1–22). Palgrave McMillan.

Boons, F. (2013). Organizing Within Dynamic Ecosystems: Conceptualizing Socio-Ecological Mechanisms. *Organization & Environment*, *26*(3), 281–297. https://doi.org/10.1177/1086026613498755

Boose, E. R., Ellison, A. M., Osterweil, L. J., Clarke, L. A., Podorozhny, R., Hadley, J. L., Wise, A., & Foster, D. R. (2007). Ensuring reliable datasets for environmental models and forecasts. *Ecological Informatics*, 2(3), 237–247. https://doi.org/10.1016/j.ecoinf.2007.07.006

Brander, M., Gillenwater, M., & Ascui, F. (2018). Creative accounting: A critical perspective on the market-based method for reporting purchased electricity (scope 2) emissions. *Energy Policy*, *112*, 29–33. https://doi.org/10.1016/j.enpol.2017.09.051

Burbano, V. C., Delmas, M. A., & Cobo, M. J. (2024). The Past and Future of Corporate Sustainability Research. *Organization & Environment*, 37(2), 133–158. https://doi.org/10.1177/10860266231213105

Burke, M., Hsiang, S. M., & Miguel, E. (2015). Global non-linear effect of temperature on economic production. *Nature*, *527*(7577), 235–239. https://doi.org/10.1038/nature15725

Butt, N., Lambrick, F., Menton, M., & Renwick, A. (2019). The supply chain of violence. *Nature Sustainability*, *2*(8), 742–747. https://doi.org/10.1038/s41893-019-0349-4

Cai, L., & Zhu, Y. (2015). The Challenges of Data Quality and Data Quality Assessment in the Big Data Era. *Data Science Journal*, 14. https://doi.org/10.5334/dsj-2015-002

Callery, P. J., & Perkins, J. (2021). Detecting False Accounts in Intermediated Voluntary Disclosure. *Academy of Management Discoveries*, *7*(1), 40–56. https://doi.org/10.5465/amd.2018.0229

Chatterji, A., & Toffel, M. W. (2010). How Firms Respond to Being Rated. *Strategic Management Journal*, *31*(9), 917–945.

Cordeiro, G. S., Arvate, P. R., Story, J., & Pongeluppe, L. S. (2023). Heroes or Villains? Agribusiness Leaders in the Amazon. *Academy of Management Discoveries*.

Cort, T., & Esty, D. (2020). ESG Standards: Looming Challenges and Pathways Forward. *Organization & Environment*, *33*(4), 491–510. https://doi.org/10.1177/1086026620945342

Cronn, R. C., Finch, K. N., Hauck, L. L., Parker-Forney, M., Milligan, B. G., Dowling, J., & Scientists, A. (2021). Range-wide assessment of a SNP panel for individualization and geolocalization of bigleaf maple (*Acer macrophyllum* Pursh). *Forensic Science International: Animals and Environments*, *1*, 100033. https://doi.org/10.1016/j.fsiae.2021.100033

Cullum, J., Stevens, D. P., & Joshi, M. M. (2016). Importance of ocean salinity for climate and habitability. *Proceedings of the National Academy of Sciences of the United States of America*, *113*(16), 4278–4283. https://doi.org/10.1073/pnas.1522034113

Delmas, M., Etzion, D., & Nairn-Birch, N. (2013). Triangulating Environmental Performance: What Do Corporate Social Responsibility Ratings Really Capture? Academy of Management Perspectives, 27(3), 255–267.

Depoers, F., Jeanjean, T., & Jérôme, T. (2016). Voluntary Disclosure of Greenhouse Gas Emissions: Contrasting the Carbon Disclosure Project and Corporate Reports. *Journal of Business Ethics*, *134*(3), 445–461.

Earthsight. (2020). IKEA's house of horrors. https://www.earthsight.org.uk/news/investigations/ikea-house-of-horrors. Accessed November 11, 2024.

Eccles, R. G., Lee, L.-E., & Stroehle, J. C. (2020). The social origins of ESG: An analysis of Innovest and KLD. *Organization & Environment, 33*(4), 575-596. https://doi.org/10.1177/1086026619888994

Ellison, A. M. (2010). Repeatability and transparency in ecological research. Ecology, 91(9), 2536–2539.

Etzion, D. (2007). Research on Organizations and the Natural Environment, 1992—Present: A Review. *Journal of Management*, *33*(4), 637–664.

Etzion, D., & Aragon-Correa, J. (2016). Big Data, Management, and Sustainability: Strategic Opportunities Ahead. *Organization & Environment*, *29*(2), 147–155.

Gacia, E., Invers, O., Manzanera, M., Ballesteros, E., & Romero, J. (2007). Impact of the brine from a desalination plant on a shallow seagrass (Posidonia oceanica) meadow. *Estuarine, Coastal and Shelf Science*, *72*(4), 579–590. https://doi.org/10.1016/j.ecss.2006.11.021

Gasson, P. E., Lancaster, C. A., Young, R., Redstone, S., Miles-Bunch, I. A., Rees, G., Guillery, R. P., Parker-Forney, M., & Lebow, E. T. (2021). WorldForestID: Addressing the need for standardized wood reference collections to support authentication analysis technologies; a way forward for checking the origin and identity of traded timber. *PLANTS, PEOPLE, PLANET*, *3*(2), 130–141. https://doi.org/10.1002/ppp3.10164

Gatignon, A., & Capron, L. (2023). The Firm as an Architect of Polycentric Governance: Building Open Institutional Infrastructure in Emerging Markets. *Strategic Management Journal*, *44*, 48–85.

Gladwin, T. N., Kennelly, J. J., & Krause, T.-S. (1995). Shifting Paradigms for Sustainable Development : Implications for Management Theory and Research. *Academy of Management Review*, 20(4), 874-907. https://doi.org/10.5465/AMR.1995.9512280024

Grégoire, D. A., Ter Wal, A. L. J., Little, L. M., Bermiss, S., Kotha, R., & Gruber, M. (2024). Mobilizing New Sources of Data: Opportunities and Recommendations. *Academy of Management Journal*, *67*(2), 289–298. https://doi.org/10.5465/amj.2024.4002

Hahn, T., Howard-Grenville, J., Lyon, T., Russo, M. V., & Walls, J. L. (2021). Leadership Forum on Organizations and Sustainability: Taking Stock, Looking Forward. *Organization & Environment*, *34*(1), 3–17. https://doi.org/10.1177/1086026621992147

Hansen, E., Panwar, R., & Vlosky, R. (2013). Understanding and Managing Change in the Global Forest Sector. In *The Global Forest Sector*. CRC Press.

Haug, A. (2021). Understanding the differences across data quality classifications: A literature review and guidelines for future research. *Industrial Management & Data Systems*, 121(12), 2651–2671. https://doi.org/10.1108/IMDS-12-2020-0756

Heath, D., Macciocchi, D., Michaely, R., & C. Ringgenberg, M. (2023). Does Socially Responsible Investing Change Firm Behavior? Review of Finance, 27(6), 2057–2083. https://doi.org/10.1093/rof/rfad002.

Hoffman, A. J., & Jennings, P. D. (2015). Institutional Theory and the Natural Environment: Research in (and on) the Anthropocene. *Organization & Environment*, *28*(1), 8–31. https://doi.org/10.1177/1086026615575331

IKEA. (2020). Summary of IKEA investigations into Ukrainian Wood Supply Chain. https://preview.thenewsmarket.com/Previews/IKEA/DocumentAssets/569809.pdf Accessed November 11, 2024.

Jasanoff, S. (2021). Humility in the Anthropocene. Globalizations, 18(6), 839–853. https://doi.org/10.1080/14747731.2020.1859743

Johnson, M. P., & Schaltegger, S. (2020). Entrepreneurship for Sustainable Development: A Review and Multilevel Causal Mechanism Framework. *Entrepreneurship Theory and Practice*, *44*(6), 1141–1173. https://doi.org/10.1177/1042258719885368

Jorgenson, A. K. (2007). Does Foreign Investment Harm the Air We Breathe and the Water We Drink? A Cross-National Study of Carbon Dioxide Emissions and Organic Water Pollution in Less-Developed Countries, 1975 to 2000. *Organization & Environment*, *20*(2), 137–156. https://doi.org/10.1177/1086026607302153

Kaplan, S., Milde, J., & Cowan, R. S. (2017). Symbiont Practices in Boundary Spanning: Bridging the Cognitive and Political Divides in Interdisciplinary Research. *Academy of Management Journal*, 60(4), 1387–1414. https://doi.org/10.5465/amj.2015.0809

Kar, D., & Spanjers, J. (2017). Transnational crime and the developing world. *Global Financial Integrity*, *53*, 53-59.

Kim, Y. H., & Davis, G. F. (2016). Challenges for Global Supply Chain Sustainability: Evidence from Conflict Minerals Reports. *Academy of Management Journal*, 59(6), 1896-1916. https://doi.org/10.5465/amj.2015.0770

Kintisch, E. (2007). Improved monitoring of rainforests helps pierce haze of deforestation. Science, 316(5824), 536-537.

Kivleniece, I., Pongeluppe, L. S., & Lazzarini, S. G. (2024). Leviathan as Client: Public vs Private Promotion of Desalination Technology to Address Water Crises. In *Academy of Management Proceedings* (Vol. 2024, No. 1, p. 20259). Valhalla, NY 10595: Academy of Management.

Kobilinsky, L., Liotti, T. F., & Oeser-Sweat, J. (2004). *DNA: Forensic and Legal Applications*. John Wiley & Sons, Ltd. https://onlinelibrary.wiley.com/doi/abs/10.1002/0471681911

Kurland, N. B., & Zell, D. (2010). Water and Business: A Taxonomy and Review of the Research. *Organization & Environment*, *23*(3), 316–353. https://doi.org/10.1177/1086026610382627

Kuzma, S., Bierkens, M. F. P., Lakshman, S., Luo, T., Saccoccia, L., Sutanudjaja, E. H., & Van Beek, R. (2023). Aqueduct 4.0: Updated Decision-Relevant Global Water Risk Indicators. *World Resources Institute*. https://doi.org/10.46830/writn.23.00061

Lahneman, B., Walls, J. L., Unter, K. M. M., & Howard-Grenville, J. (2025). (Re)focusing on planetary boundaries for corporate sustainability research. *Strategic Organization*. https://doi.org/10.1177/14761270251315632.

Leahey, E., Beckman, C. M., & Stanko, T. L. (2017). Prominent but less productive: The impact of interdisciplinarity on scientists' research. Administrative Science Quarterly, 62(1), 105–139.

Lehner, B., & Grill, G. (2013). Global river hydrography and network routing: Baseline data and new approaches to study the world's large river systems. *Hydrological Processes*, *27*(15), 2171–2186. https://doi.org/10.1002/hyp.9740

Liesen, A., Hoepner, A. G., Patten, D. M., & Figge, F. (2015). Does stakeholder pressure influence corporate GHG emissions reporting? Empirical evidence from Europe. *Accounting, Auditing & Accountability Journal*, *28*(7), 1047–1074. https://doi.org/10.1108/AAAJ-12-2013-1547

Lyon, T. P., Delmas, M. A., Maxwell, J. W., Bansal, P., Chiroleu-Assouline, M., Crifo, P., Durand, R., Gond, J.-P., King, A., Lenox, M., Toffel, M., Vogel, D., & Wijen, F. (2018). CSR Needs CPR: Corporate Sustainability and Politics. *California Management Review*, *60*(4), 5–24. https://doi.org/10.1177/0008125618778854

Mattingly, J. E., & Berman, S. L. (2006). Measurement of Corporate Social Action: Discovering Taxonomy in the Kinder Lydenburg Domini Ratings Data. *Business & Society*, *45*(1), 20–46.

McGahan, A. M., & Pongeluppe, L. S. (2023). There is No Planet B: Aligning Stakeholder Incentives to Preserve the Amazon Rainforest. *Management Science*, *69*(12), 7860–7881.

Miola, A., & Schiltz, F. (2019). Measuring sustainable development goals performance: How to monitor policy action in the 2030 Agenda implementation? Ecological Economics, 164, 106373. https://doi.org/10.1016/j.ecolecon.2019.106373

Mortier, T., Truszkowski, J., Norman, M., Boner, M., Buliga, B., Chater, C., Jennings, H., Saunders, J., Sibley, R., Antonelli, A., Waegeman, W., & Deklerck, V. (2024). A framework for tracing timber following the Ukraine invasion. *Nature Plants*, *10*(3), 390–401. https://doi.org/10.1038/s41477-024-01648-5

Murcia, M. J., Panwar, R., & Tarzijan, J. (2020). Socially Responsible Firms Outsource Less. *Business & Society*, *60*(6), 1507-1545.

Nagaraj, A. (2022). The Private Impact of Public Information: Landsat Satellite Maps and Gold Exploration. *Management Science*, *68*(1), 564–582. https://doi.org/10.1287/mnsc.2020.3878

Natividad, G. (2014). Integration and productivity: Satellite-tracked evidence. *Management Science*, 60(7), 1698–1718. https://doi.org/10.1287/mnsc.2013.1833

Ng, C. H., Ng, K. K. S., Lee, S. L., Zakaria, N.-F., Lee, C. T., & Tnah, L. H. (2022). DNA databases of an important tropical timber tree species Shorea leprosula (Dipterocarpaceae) for forensic timber identification. *Scientific Reports*, *12*(1), 9546. https://doi.org/10.1038/s41598-022-13697-x

Nilashi, M., Boon, O. K., Tan, G., Lin, B., & Abumalloh, R. (2023). Critical Data Challenges in Measuring the Performance of Sustainable Development Goals: Solutions and the Role of Big-Data Analytics. Harvard Data Science Review, 5(3). https://doi.org/10.1162/99608f92.545db2cf

Nonato LG, Russo V, Costa B, Moreno-Vera F, Toledo G, de Jesus OB, Vieira R, Lentini M, Poco J. (2025). Assessing timber trade networks and supply chains in Brazil. *Nat Sustain, 8,* 215–220 . https://doi.org/10.1038/s41893-024-01491-8

Olson, S., Jansen, M. F., Abbot, D. S., Halevy, I., & Goldblatt, C. (2022). The Effect of Ocean Salinity on Climate and Its Implications for Earth's Habitability. *Geophysical Research Letters*, *49*(10), 1–9. https://doi.org/10.1029/2021GL095748

Omri, N., Al Masry, Z., Mairot, N., Giampiccolo, S., & Zerhouni, N. (2020). Industrial data management strategy towards an SME-oriented PHM. *Journal of Manufacturing Systems*, *56*, 23–36. https://doi.org/10.1016/j.jmsy.2020.04.002

Ostrom, E., & Nagendra, H. (2006). Insights on linking forests, trees, and people from the air, on the ground, and in the laboratory. *Proceedings of the National Academy of Sciences of the United States of America*, *103*(51), 19224–19231. https://doi.org/10.1073/pnas.0607962103

Otto, I. M., Donges, J. F., Cremades, R., Bhowmik, A., Hewitt, R. J., Lucht, W., Rockström, J., Allerberger, F., McCaffrey, M., Doe, S. S. P., Lenfernal, A., Moránm, N., van Vuureno, D. P., & Schellnhuber, H. J. (2020). Social tipping dynamics for stabilizing Earth's climate by 2050. Proceedings of the National Academy of Sciences, 117(5), 2354–2365.

Panwar, R., Pinkse, J., Cashore, B., & Husted, B. W. (2023). Why corporate sustainability initiatives fail to reduce deforestation and what to do about it. *Business Strategy and the Environment*, *32*(8), 5121–5127. https://doi.org/10.1002/bse.3421

Parris, T. M., & Kates, R. W. (2003). Characterizing and measuring sustainable development. *Annual Review of Environment and Resources*, 28(1), 559-586.

Pasquier, T., Lau, M. K., Trisovic, A., Boose, E. R., Couturier, B., Crosas, M., Ellison, A. M., Gibson, V., Jones, C. R., & Seltzer, M. (2017). If these data could talk. Scientific Data, 4(1), 170114. https://doi.org/10.1038/sdata.2017.114

Price, E. R., Miles-Bunch, I., Gasson, P. E., & Lancaster, C. A. (2021). Inference of origin of *Pterocarpus* timber by chemical profiling of ambient ionization mass spectra. *Forensic Science International: Animals and Environments*, *1*, 100032. https://doi.org/10.1016/j.fsiae.2021.100032

Price, E. R., McClure, P. J., Huffman, A. N., Voin, D., & Espinoza, E. O. (2022). Reliability of wood identification using DART-TOFMS and the ForeST© database: A validation study. *Forensic Science International: Animals and Environments*, *2*, 100045.

Rau, H., Goggins, G., & Fahy, F. (2018). From invisibility to impact: Recognising the scientific and societal relevance of interdisciplinary sustainability research. *Research Policy*, *47*(1), 266–276. https://doi.org/10.1016/j.respol.2017.11.005

Richardson, K., et al. (2023). Earth beyond six of nine planetary boundaries. *Science Advances,* 9(37). https://doi.org 10.1126/sciadv.adh2458

Russo, M. V., Louche, C., & Wagner, M. (2024). A Solid Foundation But What Will Be Built on It? Reviews of the Management, Organizations, and Environmental Sustainability Field. *Organization & Environment*, 37(2), 119–132. https://doi.org/10.1177/10860266241264262

Savage, S. (2016). Using DNA To Fight Fabric Fraud. *Forbes*. https://www.forbes.com/sites/stevensavage/2016/02/12/using-dna-to-fight-fabric-fraud

Saunders, J, & Norman, M. (2020). Conflict, Fragility, and Global Fragility in High-Risk Timber. *Forest Trends*.

Schaltegger, S., Christ, K. L., Wenzig, J., & Burritt, R. L. (2022). Corporate sustainability management accounting and multi-level links for sustainability – A systematic review. *International Journal of Management Reviews*, *24*(4), 480–500. https://doi.org/10.1111/ijmr.12288

Shandra, C. L., Shandra, J. M., & London, B. (2011). World Bank Structural Adjustment, Water, and Sanitation: A Cross-National Analysis of Child Mortality in Sub-Saharan Africa. *Organization & Environment*, *24*(2), 107–129. https://doi.org/10.1177/1086026611413931

Sharma, S. (2022). From Environmental Strategy To Environmental Impact. *Academy of Management Discoveries*, 8(1), 1–6. https://doi.org/10.5465/amd.2019.0274

Shrivastava, P., Kasuga, F., & Grant, J. (2023). From climate science to climate action. *Global Sustainability*, 6, e21. https://doi.org/10.1017/sus.2023.19

Slager, R., & Gond, J.-P. (2022). The Politics of Reactivity: Ambivalence in corporate responses to corporate social responsibility ratings. *Organization Studies*, *43*(1), 59–80. https://doi.org/10.1177/0170840620964980

Souza-Rodrigues, E. (2019). Deforestation in the Amazon: A Unified Framework for Estimation and Policy Analysis. *The Review of Economic Studies*, *86*(6), 2713–2744. https://doi.org/10.1093/restud/rdy070

Talbot, D., & Boiral, O. (2018). GHG Reporting and Impression Management: An Assessment of Sustainability Reports from the Energy Sector. *Journal of Business Ethics*, *147*(2), 367–383. https://doi.org/10.1007/s10551-015-2979-4

Tnah, L. H., Lee, S. L., Ng, K. K. S., Faridah, Q.-Z., & Faridah-Hanum, I. (2010). Forensic DNA profiling of tropical timber species in Peninsular Malaysia. *Forest Ecology and Management*, *259*(8), 1436–1446. https://doi.org/10.1016/j.foreco.2010.01.017

Van de Ven, A. H. (2010). *Engaged scholarship : A guide for organizational and social research* (Reprinted). Oxford University Press.

van Westen, R. M., Kliphuis, M., & Dijkstra, H. A. (2024). New Physics-Based Early Warning Signal shows AMOC is on Tipping Course. *Science Advances*, *10*, 1–11. https://doi.org/10.1126/sciadv.adk1189

Varsano, L., & Kruitwagen, L. (2023, November 2). *Views from above: Gary Works (U.S. Steel), Gary, IN, USA - Climate TRACE*. https://climatetrace.org/news/views-from-above-gary-works-us-steel-gary-in-usa

Vedula, S., Doblinger, C., Pacheco, D., York, J., Bacq, S., Russo, M., & Dean, T. (2022). Entrepreneurship for the Public Good: A Review, Critique, and Path Forward for Social and Environmental Entrepreneurship Research. *Academy of Management Annals*, 16(1), 391–425. https://doi.org/10.5465/annals.2019.0143

Wang, R. Y., & Strong, D. M. (1996). Beyond Accuracy: What Data Quality Means to Data Consumers. *Journal of Management Information Systems*, *12*(4), 5–33. https://doi.org/10.1080/07421222.1996.11518099

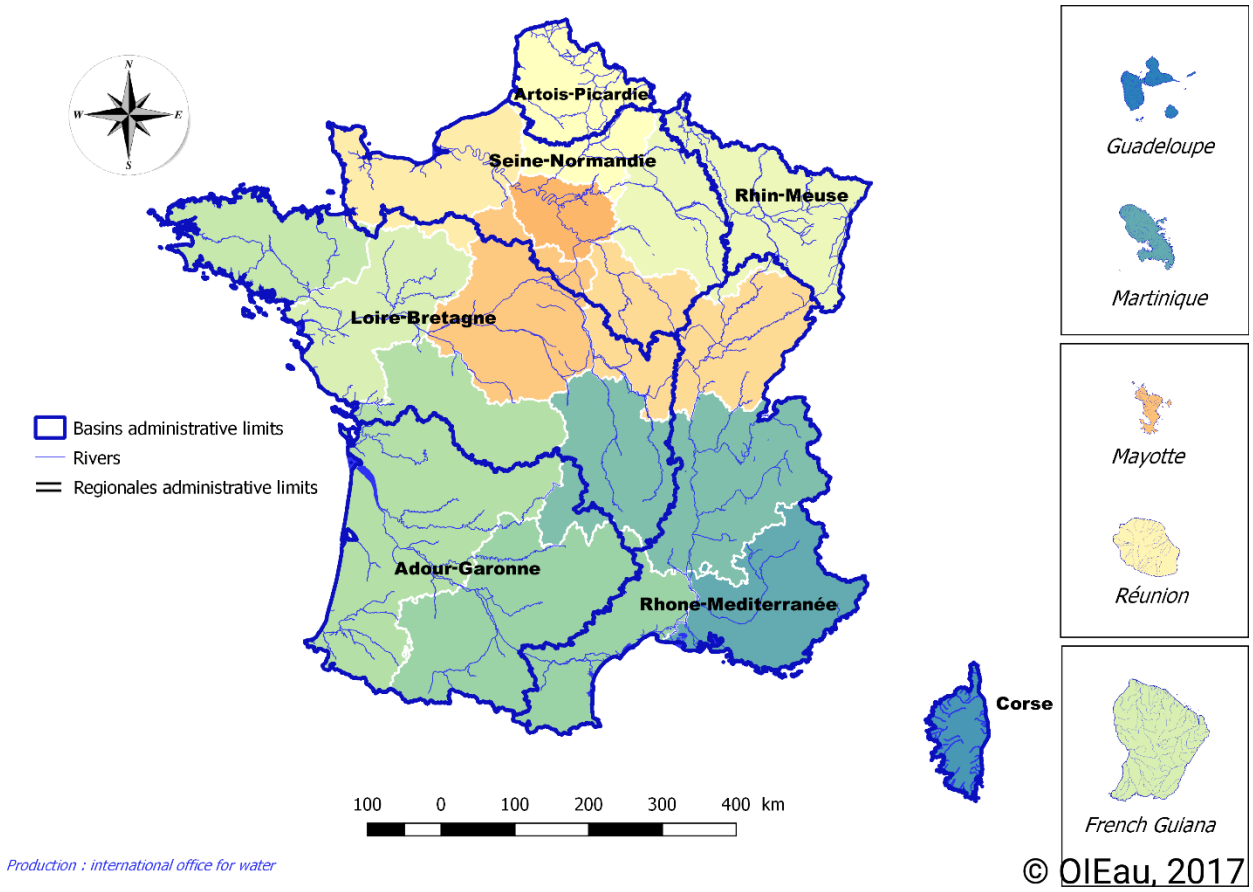
Wheeler, E.A. (2011). InsideWood – A Web Resource for Hardwood Identification. *IAWA Journal* 32(2): 199-211.

Wheeler, E.A., P.E. Gasson, & Baas. P. (2020). Using The InsideWood Web Site: Potentials and Pitfalls. *IAWA Journal* 41 (4): 412-462.

Williams, A., Perego, P., & Whiteman, G. (2025). Boundary Conditions for Organizations in the Anthropocene: A Review of the Planetary Boundaries Framework 10 Years On. *Journal of Management Studies*. 62(4), 1811-1846. https://doi.org/10.1111/joms.13150

Figure 1

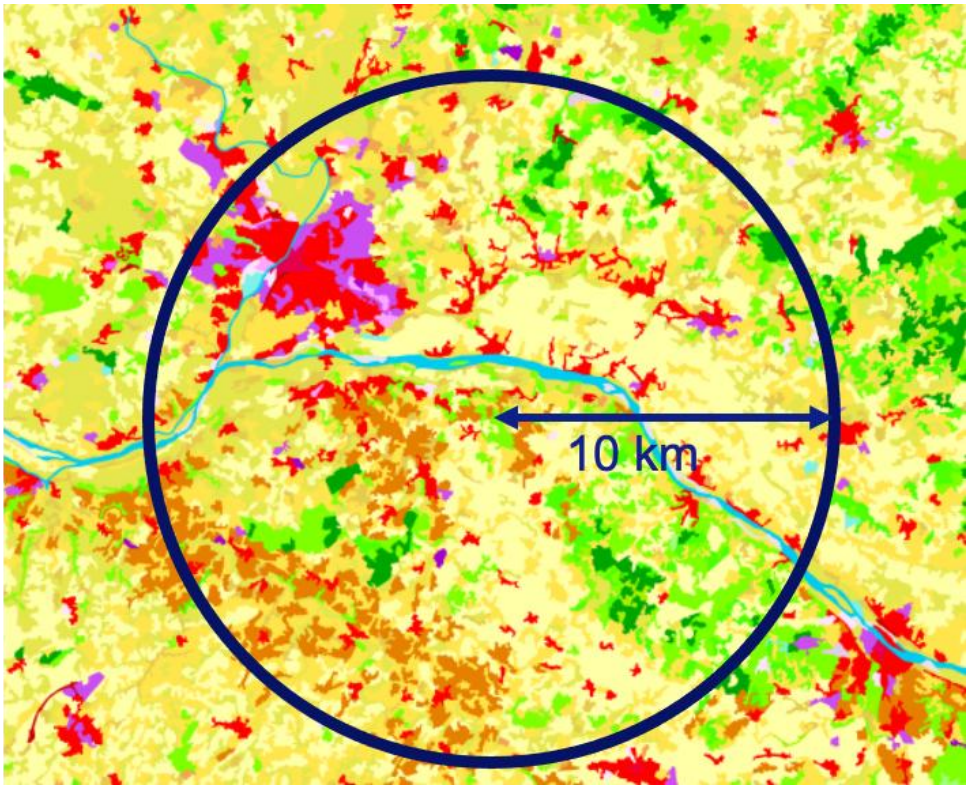
Administrative Regions (in Different Colors) vs. Hydrographic Basins (Delineated in Blue) in France.



Note: Data sourced from OIEau, 2017, CC BY 3.0 FR

Figure 2

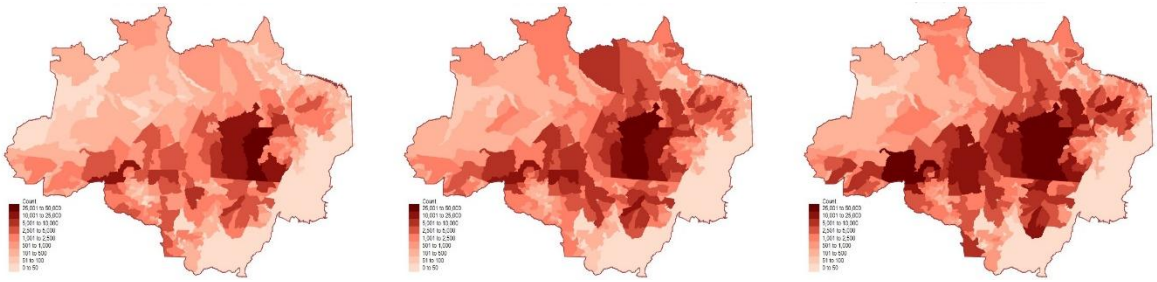
CORINE Land Cover 2018 Data Visualization



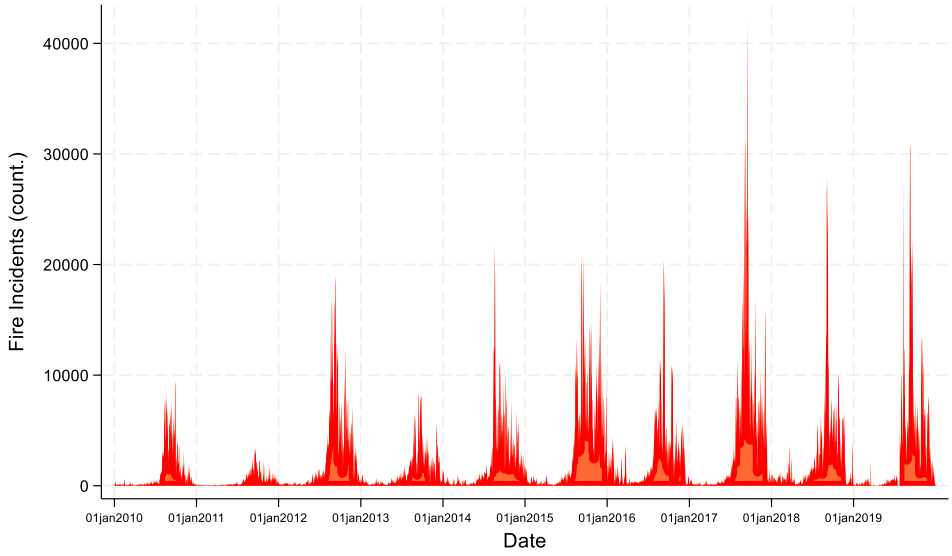
Note: Shades of red/pink represent developed land, shades of yellow to brown are various types of agricultural land and shades of green are forest ad semi-natural land. Figure elaborated based on the Copernicus visualization website. © OpenStreetMap (and) contributors, CC-BY-SA | No Limitation. Full data visualization and a legend can be found at: https://land.copernicus.eu/en/map-viewer?dataset=0407d497d3c44bcd93ce8fd5bf78596a

Figure 3

Fire Incidents in the Brazilian Amazon Rainforest



Panel A: Number of fire incidents in 2010, 2014, and 2019, by municipality

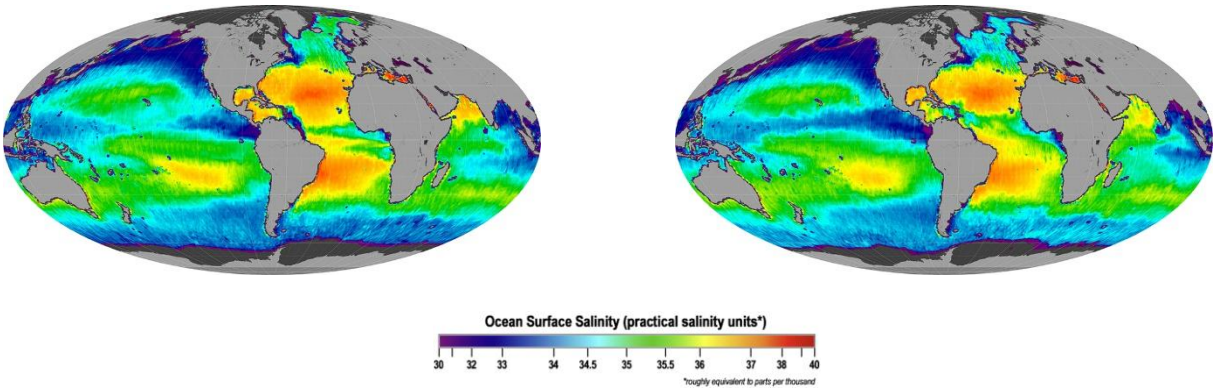


Panel B: Number of fire incidents: Daily evolution from January 1, 2010 to December 31, 2019

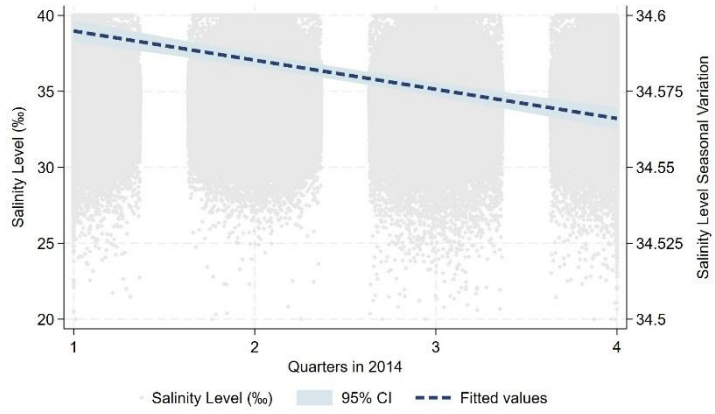
Note: Data sourced from INPE Queimadas; visualizations produced by the author.

Figure 4

Ocean Surface Salinity Levels in 2014



Panel A: Average salinity levels (‰) in June 2014 and December 2014

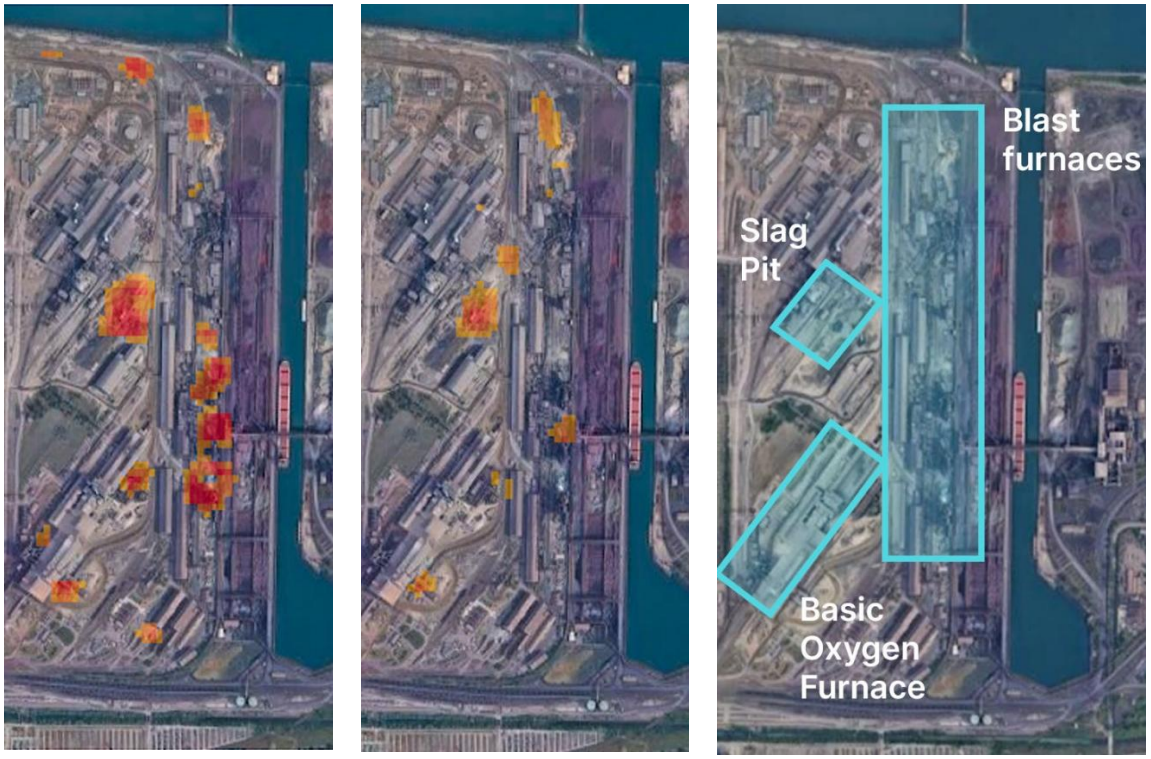


Panel B: Salinity levels (‰), quarterly evolution in 2014

Note: Data sourced from the NASA Aquarius Mission. Panel A uses images from the NASA Aquarius Mission (available for educational purposes at the NASA Sea Surface Salinity Gallery <https://aquarius.oceansciences.org/cgi/gal_salinity.htm#mission>). Panel B produced by the author.

Figure 5

Infrared Heat Signatures

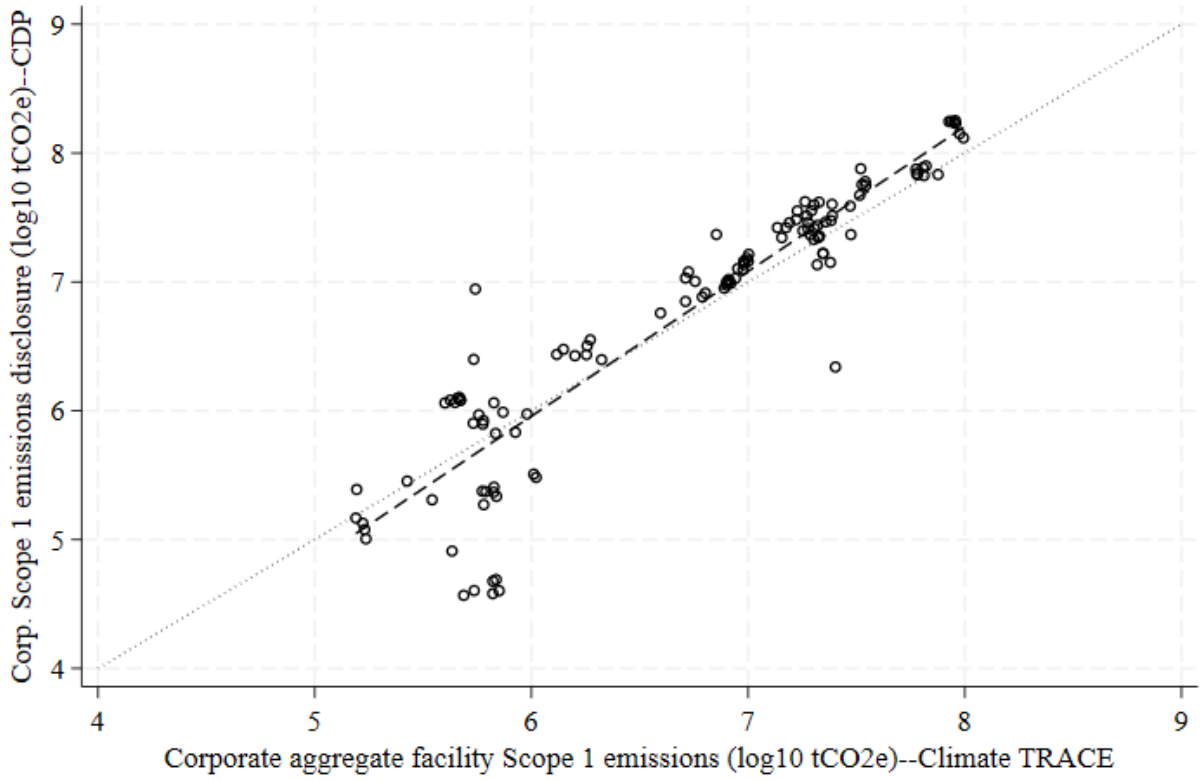


(a) Early 2020 (b) May 2020 (c) Facility sub-assets

Note: Satellite images showing infrared heat signatures of a typical steel plant (a) at normal production levels and (b) during the COVID pandemic slowdown. The variable heat signatures of different sub-assets within the facility's boundaries enable segregation into separate activities, each with its own CO2 emissions factors, improving accuracy of estimates. Sentintel-2A/B and Landsat-8/9 images courtesy of Climate TRACE (Varsano & Kruitwagen, 2023). Landsat-7 images courtesy of the U.S. Geological Survey. Copernicus Sentinel satellite stills processed by European Space Agency under the Open Access compliant Creative Commons CC BY-SA 3.0 IGO license.

Figure 6

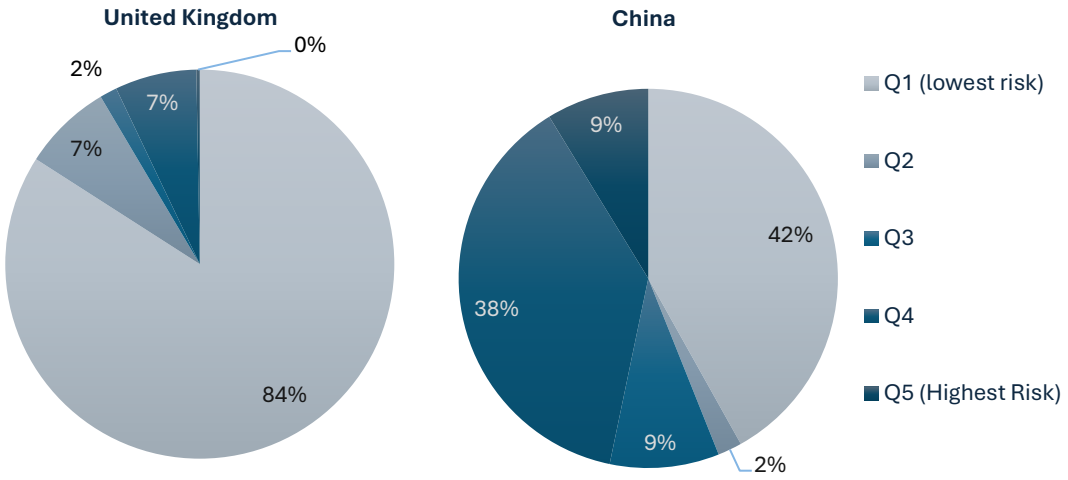
Climate TRACE Estimated Emissions vs. CDP Emissions Disclosures



Note: Scatter plot of corporate parent aggregate facility-level Scope 1 emissions ($\log_{10}$ tons CO_2e) estimated by Climate TRACE (x-axis) versus corporate parent Scope 1 emissions disclosure from CDP (y-axis). The dotted line is 45°; the dashed line is a linear fit.

Figure 7

Total Import Risk Analysis of Forest Products (2015-2020)



Note: Import risk analysis of timber forest products (excludes pulp and paper) for the importing countries, United Kingdom and China, from 2015-2020. Downloaded June 20, 2024 from Forest Trends' ILAT Risk website, https://www.forest-trends.org/idat/ilat-risk-data-tool/

Table 1

The 10 Largest Steel Parent Companies by Production Output (2022)

Parent company	Country	No. facilities	Capacity (Mt)	Steel output (Mt)	Scope 1 emissions ($MtCO_2e$)	Intensity (t CO_2e/ t output)	CDP emissions ($MtCO_2e$)
ArcelorMittal	Luxem.	34	104.0	67.3	98.6	1.5	131.1
Nippon Steel	Japan	12	52.7	39.6	74.1	1.9	--
POSCO Holdings	Korea	3	40.4	37.6	64.1	1.7	77.1
Baoshan Iron & Steel	China	3	36.0	28.3	44.0	1.6	--
JFE Holdings	Japan	9	35.7	25.4	43.3	1.7	--
China Baowu Steel Group	China	11	34.1	23.8	36.7	1.5	--
Angang Steel	China	3	27.3	20.9	32.5	1.6	--
Nucor	USA	16	24.3	20.2	5.0	0.2	--
Beijing Jianlong Investments	China	11	28.2	20.0	31.1	1.6	--
Ansteel Group	China	5	21.7	18.7	26.8	1.4	--

Note: Data sourced from Climate TRACE. Facility ownership and capacity data sourced from Global Energy Monitor, via Climate TRACE. Facility output data sourced from Worldsteel, via Climate TRACE. CDP emissions sourced from CDP. Note that most firms use primarily blast furnace production, whereas Nucor uses almost exclusively electric arc furnace production, which generates Scope 2 emissions, hence its lower Scope 1 emissions intensity.

Table 2

Sample research questions that environmental datasets can enable

	Hydrological	Forest satellite	Ocean satellite	GHG satellite	Timber trade
Regulatory effects	Does regulation reduce water risk for companies and local communities?	Do national regulations affect deforestation rates in the Amazon rainforest?	Can international regulations contribute to protecting marine biodiversity?	How do changes in jurisdictional carbon pricing affect facility-level allocation decisions for multinational enterprises (e.g., is there "leakage")?	What are the risk assessments of traded products and trade partners?
Self-regulation / corporate target setting	Do companies adapt their operations depending on the biophysical condition of the hydrological basins in which they are located?	Can companies operating in the Amazon rainforest internalize positive/negative externalities generated by their operations?	How do companies use scientific datasets to understand and remediate their ecological footprints?	Are company claims of low-carbon technology implementation supported by direct observation?	Can claims of product origin be verified?
Corporate disclosure accuracy / veracity		Does forestry satellite imagery support the impact firms claim in their annual and sustainability reports?	Is desalination technology indeed a sustainable solution to fresh water scarcity?	How are observed changes in facility-level emissions related to corporate emissions disclosure choices?	How can organizations in plant-based sectors stop unsustainable resource extraction?
Supply chains / value chains	How do companies with long supply chains account for water issues in their risk management practices?	What is corporate supply chain's impact on preserving the Amazon rainforest?	What are the potential effects of desalination on the value chain of industries such as fishing?		How do companies in plant-based sectors trace products through opaque supply chains?

Table 3

Trade-offs in the use of direct-observation datasets for ONE research

Dataset	Accessibility	Intrinsic Quality	Contextual Relevance	Interpretability
HydroBASINS	High: open access.	High: Peer reviewed GIS datasets.	Moderate: basin boundaries worldwide.	Low: hydrological measures.
Aqueduct	High: open access.	Moderate: Peer reviewed data assembled by World Resources Institute data.	Moderate: oriented to agriculture, extreme events and nation states.	Moderate: water risks such as floods, droughts and stress.
INPE DETER and Queimadas	High: open access.	High: satellite measures from Brazilian Space Research Institute, mandated by law.	Moderate: geolocated to Amazonian municipalities.	High: Forested areas (in km^2) and number of fire incidents (count).
NASA Aquarius Mission	High: open access.	High: satellite measures from National Aeronautics and Space Administration.	Moderate: global coverage of all oceanic latitudes and longitudes.	Moderate: Salinity (in ‰) and temperature (in C^o).
Climate TRACE Emissions	High: open access.	Moderate: machine learning data derived from satellite measures of GHG emissions.	High: geolocated individual emission sources (e.g. facilities) from 10 sectors.	High infrared imagery providing Scope 1 emission assessment.
Global Illegal Logging and Associated Trade Risk Data Tool (ILAT)	High: open access.	Low: Nation level corruption, governance, political and timber harvest risk measures.	Moderate: Identifies processors, producers, and trade routes.	Moderate: risk metrics for supply chain.
InsideWood, POWO, Tree of Life Explorer	Moderate: open access, except DNA traceability.	High: Peer reviewed anatomic and genomic botanical science.	Low: Identification and matching of species with likely geographic origins.	High: wood taxonomy identification, likely geographic origin.

Endnotes

[1] In this brief overview, I do not address the question of subterranean water resources (groundwater), not because it is irrelevant or no data is available, but because this data might be much harder to relate to businesses' activities, with more distant causal mechanisms.

[2] https://www.wri.org/aqueduct. Examples of how academics and corporations use the dataset are available at: https://www.wri.org/aqueduct/user-stories.

[3] https://wbwaterdata.org/ The World Bank Water Data website gathers over 2,500 datasets from 72 sources. The datasets included are very diverse in quality, scope and topic, covering issues of water quantity, quality, or infrastructures, in varied geographies. Most of the data is under a Creative Commons license. This is a valuable tool to get a sense of the kind of data available, but will not necessarily be exhaustive. The absence of a kind of data from the platform does not necessarily mean the data cannot be accessed otherwise.

[4] https://naiades.eaufrance.fr/ The French Naïades database is a public platform that centralizes and provides access to water quality and aquatic biodiversity data across France. It compiles information from various monitoring programs, and includes chemical, physical, and biological assessments of surface water bodies. The database promotes open data sharing to enhance scientific research and environmental protection efforts.

[5] https://www.hydro.eaufrance.fr/ The French public Hydro database is a national repository for hydrological data, providing access to real-time and historical information on river flows, water levels, and related hydrometric measurements across France. Similarly to Naïades, the data is open access.

[6] https://land.copernicus.eu/en/products/corine-land-cover The CORINE (Coordination of Information on the Environment) program is an EU-funded effort to develop a standardized

methodology for producing reliable land cover on a European scale. It covers 44 thematic classes of land cover, in five main categories (artificial, agricultural, forest and semi-natural, wetland, water bodies). It is edited every 6 years.

[7] https://terrabrasilis.dpi.inpe.br/en/home-page/ Researchers interested in forest conservation and deforestation should look for downloads in the "Deforestation Dashboard: PRODES" area. PRODES is a Brazilian program that traces and registers yearly deforestation. Microdata is at the municipality level, covering all 760 Brazilian Amazonian municipalities from 2000 to 2023 (most recent data available). Users can download the data in CSV or ShapeFile formats, granting them flexibility in the software they want to use in their subsequent analysis.

[8] For these data, researchers should navigate to the download area and search for the "Active Fires: DETER" area. DETER is a Brazilian program that traces and registers daily fire incidents with a more than 30 meters resolution. Researchers should look for "Queimadas," which means forest fires in English. Data can be downloaded at the municipality level from 2004 to 2024 (most recent data available). Herre too, users can choose to download the data in CSV or ShapeFile formats.

[9] Data on the salinity level of global oceans is publicly available on the NASA webpage at the Physical Oceanography Distributed Active Archive Center (PODAAC, https://podaac.jpl.nasa.gov/cloud-datasets). The webpage has a search box where scholars can describe which measures they are interested in. The system has data about ocean salinity, temperature, density, and atmospheric pressure, among others. Notice that NASA requires researchers to create a username to download the microdata, but there is no cost. Data is available for 169,137 unique oceanic locations daily from January 1st, 1992, to January 1st, 2018 (most recent data available).

[10] Data is freely available for download via the Climate TRACE website, https://climatetrace.org/data. Users can download bulk data in csv format, with each subsector methodology available in pdf document format. In addition, Climate TRACE provides an API for interacting with data. Climate TRACE also provides download packages by individual countries (all sectors included) to enable region-specific analyses. Each data download package contains data dictionary and a schema outlining the organization of unique data fields within its common reporting format. The website includes a detailed FAQ section.

[11] Note that agriculture and forestry sources comprise the bulk of Climate TRACE assets. Its global coverage of emissions generating industrial facilities, although numerically much smaller, is comprehensive.

[12] The Forest Trends Global Illegal Logging and Associated Trade Risk Data Tool (ILAT Risk Data Tool) https://www.forest-trends.org/idat/ilat-risk-data-tool/ tracks global timber and pulp & paper trade flows. It provides data at country, region and products levels of analysis.

[13] The UK Office of Product Safety and Standards UK "Timber Regulations: Due Diligence Tool 2025" provides a framework for companies to assess risk in their supply chains.

[14] The InsideWood Database, https://insidewood.lib.ncsu.edu/, integrates wood anatomical information standardized to the International Association of Wood Anatomists (IAWA) features lists. The database can be searched in several different ways making it accessible for advanced and inexperienced anatomists. All of the data is open access and users can select descriptions to export as excel documents for reference or for data analysis.

[15] Plants of the World online (POWO) https://powo.science.kew.org is a repository for the digitized data of the world's flora and fauna. POWO can be used to search for historic and current research on specific botanical taxa, in accordance with the World Checklist of Vascular

Plants (WCVP) framework. Data include a map showing the endemic (native range) of a species, herbarium sheets for identifying leave and fruit, microscopy slides for anatomical identification, general information with citations and references to global herbaria and the samples.

[16] The Kew Tree of Life Explorer, https://treeoflife.kew.org, provides evolutionary trees of flowering plants and fungi, along with open access to the underlying genomic data. This resource can be used to download all genomic data and trees.

[17] Additional databases we are aware of, but have not investigated, cover coral: https://www.coris.noaa.gov/monitoring/ , fishing: https://blog.google/outreach-initiatives/sustainability/global-fishing-watch-ai-data-human-activity-map , floods: http://global-flood-database.cloudtostreet.info , ocean plastics: https://earth.esa.int/eogateway/missions/worldview-3 and methane: https://grist.org/accountability/satellites-identify-methane-emissions-climate-pollutant .