

Biodiversity Impacts of Renewable Energy

Haozhou Gong, Chen Lin, Zacharias Sautner, Thomas Schmid*

March 9, 2026

ABSTRACT

Renewable energy (RE) is vital for addressing climate change, but the land use of hydro, solar, and wind plants can negatively affect biodiversity through habitat destruction. By combining spatial biodiversity data, satellite imagery, and asset-level information on 40,911 RE plants, we develop a novel measure of RE's biodiversity impact around the world. We find that solar plants cause the greatest negative impact overall, while hydro plants are located in the most biodiversity-sensitive areas. The biodiversity impact of RE has grown substantially over time, driven by increased land use and siting in more biodiversity-sensitive locations. The top 1% of plants and owners are responsible for the majority of the impact. We use our measure in three corporate finance applications. Publicly-listed and non-financial ownership, as well as balance-sheet financing, are each associated with siting RE projects in higher-impact locations, while private and financial ownership, as well as project finance, align with lower-impact siting choices. These results suggest that ownership structure and financing design translate into systematically different environmental footprints in project siting.

*Haozhou Gong, Chen Lin, and Thomas Schmid (corresponding author, schmid@hku.hk) are at the University of Hong Kong. Zacharias Sautner is at the University of Zurich and the Swiss Finance Institute. We are very grateful to Haotian Feng for outstanding research assistance. We also thank seminar participants at the Academy of Mathematics and Systems Science of Chinese Academy of Sciences. Sautner is on the Sustainability Council of Lampe Asset Management and a Regular Research Visitor at the European Central Bank.

I. Introduction

The transition towards renewable energy (RE) is the central pillar of climate change mitigation. According to the International Renewable Energy Agency (IRENA), investments in RE need to more than double from \$624 billion in 2024 to \$1.4 trillion per year over the 2025–2030 period to meet globally agreed climate targets (IREA, 2025). Parts of the demand for RE are due to the AI boom, which requires massive amounts of electricity to power data centers, and many AI companies have made commitments to use renewable sources to meet their energy needs (e.g., Nvidia, 2025). Yet this transition can generate significant and often underexamined tradeoffs with biodiversity conservation because RE investments can involve environmental costs if RE plants negatively affect biodiversity by destroying habitats or fragmenting ecosystems through infrastructure. Consistent with the materiality of these impacts, Giglio et al. (2025) document that RE producers are among the most frequent disclosers of biodiversity-related risks in their Form 10-K annual reports. This indicates that solutions to the climate change challenge can come with unintended consequences for biodiversity loss. Operators of RE plants and investors become increasingly aware of these complex interrelations, and some actively consider ways to address the associated tradeoffs in their investment decisions.¹ Evidence also suggests that these interactions are beginning to be reflected in asset prices: Stroebel and Zeng (2025) document that RE projects aimed at hedging investor portfolios against climate transition risks simultaneously expose investors to biodiversity risks.

How the tradeoffs between RE and biodiversity loss are identified, measured, and managed is therefore a fundamental research question, particularly for finance, which plays a critical role in allocating capital and shaping the design of RE projects. Notably, financial markets, investors, and intermediaries increasingly rely on environmental metrics, risk assessments, and sustainability frameworks to evaluate renewable energy investments, but these tools often prioritize carbon reduction while insufficiently accounting for biodiversity impacts. Understanding how finance evaluates, prices, and mitigates the climate–biodiversity tradeoff is therefore important for assessing whether capital allocation mechanisms promote truly sustainable outcomes or instead shift environmental risks across dimensions.

Despite the fundamental importance of this topic, large scale, comprehensive evidence

¹Asset manager NextEnergy Group, for example, which focuses on the development, operation and financing of RE assets, has developed a nature strategy that includes the commitment that their investments do not contribute to the conversion of natural ecosystems (NextEnergy, 2025).

on the biodiversity impacts of RE is lacking, largely because of measurement challenges. Existing studies are either geographically limited or lack a standardized measurement of biodiversity impacts, which constrains the comparability of their results across regions, technologies, and time (e.g., [Cryan et al., 2014](#); [Hernandez et al., 2015](#); [Kruitwagen et al., 2021](#)). We make significant progress in addressing these challenges by (i) constructing a novel global measure of the land-use-induced biodiversity impacts of RE power plants, combining power plant location, remote sensing, and biodiversity data, and (ii) applying this newly-constructed metric in three corporate finance settings.² To measure land-use-induced biodiversity impacts, we rely on the Threat-Abatement STAR score (or $STAR_T$) score, which was introduced by [Mair et al. \(2021\)](#) and is a key metric proposed by the Taskforce on Nature-related Financial Disclosures (TNFD) and Finance for Biodiversity Foundation to evaluate the biodiversity impacts of firms and investors. Using a spatially explicit framework at a granular 5 by 5 km² level, this metric quantifies how much species extinction risk could be reduced if biodiversity threats were removed. This enables us to quantify biodiversity impacts that could have been avoided had a RE plant not been built. High $STAR_T$ scores in an area indicate locations with relatively many threatened species, a large proportion of individual species’ ranges, or species that are severely threatened.³

We combine $STAR_T$ data with information on all 40,911 solar, wind, and hydro plant units with a capacity of at least one megawatt (MW) that were newly constructed between 2000 and 2023. The overall electricity capacity of these plants is 1.37 terawatts (TW), exceeding today’s 1.30 TW electricity generation capacity in the U.S. ([APPA, 2025](#)). We identify the exact location of power plant units, calculate their land use with remote sensing data or capacity-based approximations, and spatially match their land-use footprints with $STAR_T$ data. Our satellite imagery-based approach enables us to quantify the biodiversity impact of each plant and to measure the exact overlap between plant footprints and species’ habitats, offering clear advantages over relying solely on point coordinates. This is critical as point coordinates often indicate administrative or office locations and reveal little about a plant’s spatial extent—imagery data instead allow us to track the true project footprint, to distinguish multi-unit clusters, and to allocate area

²Biodiversity pressures from land use constitute the single most important channel through which business activities negatively impact biodiversity, ahead of greenhouse gas emissions, water pollution, or toxic emissions ([Garel et al., 2024](#)).

³Two other biodiversity footprinting metrics proposed by the Finance for Biodiversity Foundation are Mean Species Abundance (MSA) and Potentially Disappeared Fraction of Species (PDF). These measures are used by data vendors such as MSCI, ISS or Iceberg Data Lab for their impact metrics and applied, for example, by [Garel et al. \(2024\)](#) to measure whether investors price the biodiversity impact of firms. These other metrics do not build on spatial data.

across adjacent plants. Furthermore, time-stamped satellite imagery allows us to verify that land conversion coincides with construction, excludes pre-existing built-up areas from biodiversity calculations, and captures before–after changes such as reservoir inundation for hydropower.⁴ This substantially reduces measurement error in siting and land-use attribution compared to coordinate-only methods. By providing a verifiable biodiversity impact measurement, our asset-level approach complements estimation-based methods (Garel et al., 2024) or disclosed-based approaches (Giglio et al., 2025).

Our quantification shows that the RE plants in our sample generate an aggregate biodiversity impact, calculated as the total $STAR_T$ score across all plants, equivalent to the value of the entire forested area in Austria or the grass land in Thailand ($STAR_T$ value of about 5 billion). Notably, biodiversity impacts of RE are heterogeneous and highly skewed: while the median plant has a low biodiversity impact ($STAR_T$ value of 1,610), the mean score of a plant ($STAR_T$ value of 129,910) is driven by a small number of projects with exceptionally large impacts. Examples include the Five Wells Solar Center, a solar power plant in the United States with a $STAR_T$ value of 327 million or the El Cajon hydropower plant in Mexico with a $STAR_T$ value of 120 million. We use IUCN Red List data to demonstrate that RE plants impact a substantial number of vulnerable and critically endangered species, with notable examples including the Leopard, the California Condor, or the Asian White-backed Vulture—all of these species lost non-trivial portions of their habitats because of RE developments. These findings demonstrate that the siting of RE projects is frequently in critical conservation areas.

We show that it is crucial to differentiate RE technologies when evaluating climate-biodiversity trade-offs. Solar and hydro plants account for nearly 90 percent of the overall biodiversity impact in our sample, with wind plants contributing relatively little. Solar plants have a large impact on biodiversity due to their large land requirements—imposing the highest total impact across all three technologies—whereas the impact of hydro plants arises primarily because such facilities are disproportionately sited in biodiversity-sensitive locations. These conclusions are unaffected if we consider capacity-scaled biodiversity impacts.

The temporal and distributional dimensions of biodiversity impacts are equally striking. Over the past two decades, biodiversity losses linked to RE expansion have risen sharply, largely because of increasing land use per project, rather than siting in more sen-

⁴The high-frequency, long-run archive data that we employ also helps filter problematic observations, such as misrecorded office coordinates, misgeolocations on water or in dense settlements, and identify plants built on already developed land (with near-zero biodiversity value).

sitive locations. Solar has overtaken hydro as the dominant driver of impacts in recent years, reflecting its rapid global deployment. Notably, impacts are highly concentrated: fewer than 1 percent of plants account for nearly 70 percent of the overall biodiversity impact of RE, and a small number of owners are responsible for a disproportionate share. These findings imply that targeted siting policies, combined with stricter biodiversity safeguards, could have substantially reduced the environmental costs of the RE transition without significantly constraining capacity growth.

An important question for the overall relevance of our analysis is how high the biodiversity impact of RE is compared to the land use for other purposes, such as roads or human settlements. For this assessment, it is important to incorporate that RE is projected to grow massively over the coming years, with estimates of the International Energy Agency predicting that RE plants will meet almost half of global electricity demand by the end of this decade. This reflects the addition of 5,500 GW of new RE capacity between 2024 and 2030 (three times the increase seen between 2017 and 2023). About 80% of the capacity growth will come from solar plants (IEA, 2024), which in our sample cause about half of the total biodiversity impact. Also on the hydro side, a surge in new projects is projected. Studies estimate that at least 3,700 major dams—each with a capacity of more than 1 MW—are planned or under construction, primarily in emerging economies (Zarfl et al., 2015). Using the planned expansion of RE capacity to 2030, we estimate that the biodiversity impact of RE could reach the scale of Canada’s total land biodiversity. Our approach is therefore not only relevant in quantifying the biodiversity impacts of existing RE projects, but can also be used when evaluating future projects. Importantly, our quantification can be applied to other assets, such as manufacturing plants or infrastructure projects. Currently, however, this is not possible at a global scale, as most firms do not report on their asset locations. This is different for energy generation plants, where comprehensive location data has been available for a decade.⁵

We illustrate how our measure can be applied in finance research using three applications. While none of these applications are intended to establish a causal relationship, they highlight important economic factors associated with the biodiversity impacts of RE plants. The first analysis contrasts the biodiversity impacts of RE plants owned by publicly-listed versus privately-held firms, motivated by prior evidence that private firms generate fewer environmental externalities due to concentrated ownership and weaker

⁵A lack of location data has been identified as a key restriction for the measurement and management of biodiversity risks, and recent disclosure frameworks therefore emphasize the importance of reporting on asset locations.

short-term market pressures (Shive and Forster, 2020). Our estimations show that plant owners that are publicly-listed entities select locations that have a two-thirds higher biodiversity impact compared to those of private owners. After controlling for plant size and capacity, the difference remains positive but narrows to under 10 percent. Our evidence is consistent with private owners placing greater weight on long-term and reputational considerations when making siting and construction decisions.

The second application examines whether financial owners differ from non-financial owners in where they locate plants. If financial institutions face relatively stronger ESG-related financial, reputational, and normative pressures—as is argued in prior literature—then they may be more attentive to biodiversity risks of their investments. Consistent with this argument, we show that plants with financial owners are sited in locations where the biodiversity impact is markedly lower. While part of this effect reflects smaller plant size, a roughly 10 percent difference remains even after controlling for area and capacity. Thus, financial owners not only develop smaller RE installations but also site them in areas with lower biodiversity sensitivity.

The third application considers debt financing and compares RE plants financed through project finance—typically structured as long-horizon, ring-fenced Special Purpose Vehicles—with those financed through corporate balance sheets. We find that project-finance plants are consistently located in places where they generate lower biodiversity impacts. This result suggests that the typically longer investment horizons of project financing structures, combined with increasingly frequent environmental due diligence by capital providers through initiatives such as the Equator Principles (Berg et al., 2024), lead to siting choices that are relatively less harmful to biodiversity.

Prior work has documented that RE requires increased land use compared to fossil fuels (Hertwich et al., 2015; Gasparatos et al., 2017; Luderer et al., 2019). However, existing studies on RE are fragmented, either focusing on single technologies, case studies, or country-level approximations. For solar plants, studies show that large-scale photovoltaic (PV) installations are disproportionately sited in shrublands, scrublands, croplands, and grasslands, which often overlap with sensitive habitats (Hernandez et al., 2015; Kruitwagen et al., 2021). Regional studies confirm negative outcomes for wildlife; for instance, bird species richness and density decline close to PV facilities in South Africa (Visser et al., 2019). For wind plants, Cryan et al. (2014) demonstrate high bat fatality rates near wind turbines, and Thaker et al. (2018) and Meng et al. (2025) show that wind farms reduce bird abundance in India and China, potentially triggering cascading trophic effects such as shifts in lizard populations. The biodiversity impact of hydropower results

mostly from dam-induced inundation and habitat fragmentation with profound ecological consequences (Gasparatos et al., 2017). Wang et al. (2025) evaluate the RE-related biodiversity loss using a countryside species-area relationship (c-SAR) model that predicts species richness based habitat area. However, their study relies on national averages rather than project-level information, which prevents differentiation based on site-specific biodiversity sensitivity and linkage to other data, such as ownership information. Furthermore, their analysis provides only a static, cross-sectional snapshot of infrastructure up to 2015, missing the major global expansion of RE, and lacks power generation capacity data entirely.

While insightful, existing studies are geographically limited, lack project-level information, and do not apply standardized measures of biodiversity impact, constraining their ability to assess the biodiversity impact of RE across regions, technologies, and time. Thus, a systematic global quantification of the biodiversity impact of RE plants remains absent, with studies describing the impact qualitatively or regionally. We make significant progress along all of these dimensions by providing a comprehensive, global assessment of the biodiversity impact of RE using a standardized biodiversity risk metric that is comparable across regions, technologies, and time.

We also contribute to a growing body of work in economics and finance that focuses on biodiversity. Flammer et al. (2025) show that blended instruments can mobilize private investment for conservation. Emerging evidence from Giglio et al. (2025) and Garel et al. (2024) suggests that biodiversity-related risks already affect equity prices. Chen et al. (2025) show that stricter enforcement of biodiversity conservation in China raised municipal borrowing costs. Frank and Sudarshan (2024) quantify the social costs of species collapse, showing that vulture declines in India imposed billions in sanitation-related damages. We contribute to this literature by providing an evaluation of the relationship between RE plants' ownership/financing and their biodiversity impact. More broadly, our research enhances this literature by introducing a novel approach to measuring the biodiversity impact of firms at the asset level. When combined with improved access to asset-level data beyond the electricity generation sector in the future, this method has the potential to address the current challenges in accurately assessing location-based biodiversity risk exposures. Such advancements can significantly advance research in this area, which has been limited by measurement difficulties (Giglio et al., 2026).

II. Quantifying Biodiversity Impacts: Data and Methodology

This section details how we identify the biodiversity impact of RE power plants by combining power plant, remote sensing, land use, and biodiversity data. We provide relatively detailed discussions, as we introduce new data and methods to the finance literature.

A. Sample Construction

We identify RE power plants using the S&P Market Intelligence (S&P MI) database, which provides comprehensive global coverage for power plant units with a capacity of at least one megawatt (MW).⁶ The dataset includes information on a plant unit’s geographic coordinates (latitude/longitude), production technology (e.g. solar photovoltaic, onshore wind, hydropower), operational status and start of commercial operations, generation capacity, equipment details, and direct as well as ultimate owners. We apply several data filters for a power plant unit to end up in our sample. First, for the scope of this study, RE includes solar photovoltaic, concentrated solar power, wind farms, and hydropower facilities (including pumped-storage); we in turn omit a few RE technologies that play only a modest role for energy production (e.g., geothermal plants). Second, we exclude power plant units for which the coordinates in the S&P database are located on water (offshore wind farms), because no comprehensive data exist to assess underwater biodiversity impacts; these restrictions apply to measuring both ocean biodiversity (Bridges and Howell, 2025) in general, and to the specific biodiversity metric employed in this paper (Mair et al., 2021). Third, we exclude projects for which the coordinates in S&P MI are located within dense human settlements, identified using the Dynamic World (Brown et al., 2022) and GAIA (Li et al., 2020) datasets, because it is often not possible to exactly locate them using satellite imagery. Fourth, we focus on power plant units that became operational between 2000 and 2023.

Our final dataset covers 40,911 RE plant units across 180 countries, consisting of 12,738 hydropower, 12,811 solar, and 15,362 wind units. For simplicity, we refer to plant *units* as *plants* (unless it is important to distinguish between the two). The RE power plants in our sample have a total capacity of approximately 1.37 TW, representing roughly 95 percent of the total utility-scale RE capacity in S&P MI in 2023.⁷

⁶Most plants consist of one plant unit but there are cases where one plant has multiple units, which can differ, for example, with regard to their generation technologies.

⁷Utility-scale RE capacity excludes small installations serving individuals or businesses, such as roof-

Figure 1 illustrates the locations of solar, wind, and hydro plants in our sample, showing that RE plants are most densely concentrated in North America, Europe, and East Asia, and that the three technologies exhibit distinct spatial patterns. Figure 2 visualizes the evolution of RE plants over time (for all plants together and separately by hydro, solar, and wind). Panel (a) reports the yearly number of newly installed plants. In the early sample years, wind and hydro were the most common technologies, while solar became more common since the 2010s. Solar overtook wind and hydro around 2015. The number of new RE plants reached a peak in 2016 and started to decline substantially afterwards. Panel (b), which reports annual added capacity, shows that despite the decline in the number of new plants, newly added capacity did not decline much over the past years, with all technologies playing a similar role in terms of the added capacity. Added capacity remained relatively constant in recent years, while the number of new plants declined, because the average capacity per plant increased substantially, as shown in Panel (c). While the average plant had a capacity of around 25 MW for most of our sample period, this number increased to about 75 MW between 2021 and 2023. Hydro has the highest average capacity, followed by wind and then solar. Solar plants experienced the most pronounced growth in average capacity, from only a few MW to more than 50 MW in 2023. Finally, Panel (d) illustrates the cumulative capacity growth, showing that today’s global utility-scale RE capacity approaches 1.5 TW, exceeding the total electricity generation capacity of the United States.

B. Remote Sensing Data

We leverage satellite imagery from two key Earth observation programs to identify and quantify the Land Use and Land Cover (LULC) change caused by the construction of RE plants. First, the Sentinel-2 mission program of the European Space Agency provides multispectral imagery with a resolution of 10 to 60 meters. Its 13 spectral bands are well-suited for our study as they provide detailed LULC classification. Furthermore, its high revisit frequency of 5 days with a two-satellite constellation ensures that land change detection is not disturbed by weather. Second, the Landsat program of NASA offers a continuous archive of Earth observation data since 1972, providing a long-term historical perspective for analyzing land change. Recent missions (Landsat 8/9) provide multispec-

top solar panels. Figure IA I 1 compares the total capacity (in gigawatt, GW) of the RE power plants in our sample (in blue) with that in the full S&P MI database (in orange) over time and across technologies. The comparisons show that our sample is highly representative, which alleviates concerns that our data filters introduce bias.

tral data primarily at 30-meter resolution with an 8-day combined revisit frequency. Both programs provide openly accessible datasets. Because Sentinel-2 offers finer spatial detail and more frequent revisits, we use their imagery for years from 2015 (it is unavailable in prior years). For satellite imagery before 2015, we use Landsat imagery.

C. Land Use Calculation

This subsection describes how we calculate the land use of solar, wind, and hydro plants and—as benchmarks—that of fossil-fuel-based and nuclear plants.

C.1. Land Use of Solar Farms

Land use for solar farms with a capacity of at least 10 MW is calculated by combining latitude/longitude information from S&P MI with Sentinel-2 satellite imagery (as of the end of 2024). The process involves several steps. First, we use the satellite imagery to search for solar panels within a 10 km buffer around each plant coordinate. Second, we employ a Random Forest machine learning algorithm on the Google Earth Engine (GEE) to classify pixels and identify solar panels. The model utilizes Sentinel-2 spectral features and is trained and validated against the Global Photovoltaics Inventory (GPI) solar panel dataset ([Kruitwagen et al., 2021](#)). To enhance detection accuracy, particularly for installations constructed after 2018 (the end of the GPI’s data coverage), we also incorporate Dynamic World LULC data ([Brown et al., 2022](#)).⁸ Third, we manually verified the land use boundaries of all identified solar farms. For inaccurate detections, we adjust the solar panel boundaries to ensure we capture the actual footprint accurately.⁹

For solar plants with a capacity below 10 MW, because their small size makes identification on satellite imagery prone to errors, we estimate land use with a log-linear regression model. This model uses a plant’s capacity and its year of commercial operation start as explanatory variables. To calibrate the model, we use the directly measured land use of solar plants with above 10 MW capacity as well as their capacity and start year of operations.

⁸Dynamic World LULC data is used to compare land cover changes between the pre- and post-installation periods, which helps us to identify and manually correct inaccuracies in the initial detection.

⁹[Figure IA I 2](#) illustrates this process. If two plants are detected within 10 km of each other, we combine their areas and allocate the land use based on their respective capacities. We apply this approach as we are unable to distinguish the land use of plants located close to each other with satellite images (see [Figure IA I 3](#) for an illustration).

C.2. Land Use of Wind Farms

The direct land use of wind farms due to turbine foundations and access roads is typically highly dispersed, making the direct detection and quantification from medium-resolution satellite data challenging.¹⁰ Therefore, we apply an indirect estimation based on data from the National Renewable Energy Laboratory (NREL) of the U.S. Department of Energy (Denholm et al., 2009; Lopez et al., 2021). These data provide verified benchmark values for the land use of U.S. wind farms. Since no comparable data are available on a global scale, we assume that the land use of wind plants in and outside the U.S. is comparable. We consider the area of the turbine pads, service roads and temporary installations that likely have a lasting impact on biodiversity. Using the NREL benchmark values, we calculate land use based on the number of wind turbines, which we determine by dividing the total plant capacity by the capacity of the specific turbine model that is used, and the land type on which they are constructed.¹¹ For units where turbine-specific data is unavailable, we estimate the land use based on their capacity, weighted land type, and the NREL benchmark values. Figure IA I 4 illustrates the process.

C.3. Land Use of Hydropower Plants

For hydro plants, the primary land use comes from the inundation caused by the reservoirs, which we quantify by measuring the change in permanent water surface area from before to after dam construction using the JRC Yearly Water Classification History dataset (Pekel et al., 2016).¹² This dataset provides high-resolution (30 meters) maps of surface water locations since 1984. The process involves several steps. First, we calculate the inundated area as the increase in permanent water surface area between the pre- and the post-construction period (using satellite imagery at the time of commercial operation compared to 10 years earlier). Second, we consider only the inundation of natural land cover types and not land types that were classified as built (urban/built-up) before the plant's construction (see Section D). Third, if a dam serves multiple facilities, we al-

¹⁰By focusing on biodiversity effects of land use, we do not directly consider the effects from birds flying into the rotors of a wind plant. However, the biodiversity metric we employ indirectly captures the biodiversity value of the birds that live in the area of a wind plant.

¹¹Turbine model information in S&P MI is available for about 70 percent of the wind plant units. The capacity per turbine is obtained from the [Wind Turbine Models](#) database. The NREL benchmark values show that land use per turbine on bareland is 12,750 m², 22,050 m² for forest, 12,075 m² for grassland, and 14,400 m² for cropland (given an average capacity of 1.5 MW per turbine).

¹²As our methodological approach focuses on horizontal impacts on habitat loss through submerged areas, we do not quantify any potential habitat impact from the vertical dimension of a dam (dam heights and dam water levels can influence ecological effects beyond the inundated surface area).

locate the total inundated natural land area among plant units based on their respective capacities (this ensures, for example, that we do not double count the biodiversity impact of a dam that operates with two turbines). [Figure IA I 5](#) illustrates the process.

C.4. Benchmarks: Land Use of Fossil-Fuel and Nuclear Plants

As benchmarks, we estimate the land use of fossil-fuel (gas, oil, coal) and nuclear plants. Although their fuel sources differ, these facilities are predominantly thermal power plants with similar land use characteristics. Because smaller fossil-fuel-based plants are difficult to locate on satellite images, we only include those with a capacity of at least 100 MW in S&P MI. We then create a training dataset of 100 medium-sized plants (between 100 and 1,000 MW) and 100 large plants (more than 1,000 MW) and measure their land use by manually delineating their boundaries in Landsat and Sentinel-2 satellite imagery. [Figure IA I 6](#) illustrates the delineated boundaries for four exemplary plants. Second, we use information on the actual land use of the plants in the training dataset to calibrate a log-linear regression model in which a plant’s capacity and year of construction serve as explanatory variables (separately for medium-sized and large plants). Third, we estimate the land use of 9,140 fossil-fuel and nuclear plants based on this calibrated model.

D. Land Type Detection

To estimate biodiversity impacts of RE plants, we need to determine the land *type* on which a facility was built. This information is important to differentiate between plants built on artificial land (like existing built-up areas with no or very little biodiversity value) and those constructed on natural/semi-natural habitats (like forest, grassland, or bare land). For years until 2020, we rely on the GLAD Global LULC dataset ([Potapov et al., 2022](#)), which is derived from the Landsat satellite data archive and quantifies changes in key land cover types with a 30-meter resolution. We reclassify their detailed land classes into seven categories: trees (forest), grass (grassland/shrubland), built (urban/built-up), bare (bare ground), crops (cropland), snow/ice, and water. For a power plant’s land use area, we then assign the corresponding land types. For years after 2020, we complement the GLAD dataset with data from the Dynamic World Project ([Brown et al., 2022](#)), which provides near-real-time global LULC classifications at 10-meter resolution using Sentinel-2 data. Additionally, we use the Global Artificial Impervious Area (GAIA) database, which was developed by [Li et al. \(2020\)](#) and maps global urban boundaries and artificial surfaces annually at a 30-meter resolution.

Table 1 shows the distribution of the seven land types associated with RE plants (across all technologies and separately for hydro, wind, and solar plants). We find that the most common land use of RE plants is grass land (29.1%), followed by forested areas (22.7%) and bare land (18.4%). Approximately one-fifth of the total area of RE plants in our sample is on already built land.¹³ Since the biodiversity value of such artificial land is virtually zero, it is important to consider this in the biodiversity impact calculation. Snow, ice, and water play a minor role for RE plants.¹⁴ When considering the individual RE technologies, forested areas are the most common land types for hydro plants (42.2%), and grass land for wind (40.2%) and solar plants (29.1%).

E. Quantifying Biodiversity Impacts

We quantify the biodiversity impacts of RE plants due to land use using the STAR metric (Mair et al., 2021). In Internet Appendix , we discuss potential alternative biodiversity metrics, such as the Biodiversity Intactness Index or Mean Species Abundance, and use two case studies to illustrate why the STAR metric is most appropriate in our context. Using a spatially explicit framework, the STAR metric assesses the possible impact of threat reduction and habitat restoration activities on decreasing the extinction risk faced by species (as species, the framework considers mammals, amphibians, and birds). The STAR metric has been validated and applied in different conservation settings to evaluate biodiversity frameworks or extinction risks (e.g., Mair et al., 2023; Asefa et al., 2025). It is therefore emerging as a critical tool for investors and firms to evaluate their biodiversity impacts. It is presented, for example, as a tool for measuring biodiversity impact by the Taskforce on Nature-related Financial Disclosures (TNFD), which provides nature-related disclosure guidelines, or the Finance for Biodiversity Foundation (FbBF), an organization supported by financial institutions representing over \$25 trillion in assets with the goal to protect biodiversity. Importantly for our purposes, the STAR metric is available at a global level and scalable across time and geographies.

The STAR metric consists of a Threat Abatement ($STAR_T$) and a Habitat Restoration ($STAR_R$) score, and we focus on $STAR_T$ because it better reflects biodiversity impacts of newly constructed energy infrastructure. STAR data is obtained via the Integrated

¹³Although we exclude RE plants if the coordinates in S&P MI are located within human settlements, it is not uncommon that RE plants are partly constructed on already built land. In this case, we allocate the land use partially to the built-land type that includes human settlements.

¹⁴The reason why some area is on water is the same as for built land; we only exclude RE plants for which the coordinates are located on water, which does not exclude the possibility that part of a plant is constructed on water.

Biodiversity Assessment Tool (IBAT).¹⁵ A high STAR_T score indicates locations that contain many threatened species, a high proportion of such threatened species’ ranges, and a high severity of threats to those species (we verify this below). As a result, measures that prevent threats to biodiversity—in our case the threats posed by new RE infrastructure—are especially effective in these regions. The STAR metric relies on the IUCN Red List of Threatened Species, which provides a globally recognized standard for assessing species’ extinction risk. The scores are available at high “pixel” granularity and for a global raster with a base resolution of 5 km—each pixel therefore represents $5 \times 5 \text{ km}^2$ on the ground. For each pixel, the proportion of a species’ global area of habitat located in that specific pixel is then calculated and weighted by its IUCN Red List category score. The STAR_T index value for each $5 \times 5 \text{ km}^2$ pixel is in turn calculated as the sum of these species-specific scores (the foundational is therefore per-se a unit-less index).¹⁶ Figure IA I 7 illustrates the global STAR_T score distribution, with blue color indicating low, and red color high, scores.

To calculate a STAR_T score for each power plant unit, we proceed in three steps. First, we overlay the calculated land-use footprint onto the global STAR_T map layer at a resolution of 5 km^2 . Second, we set STAR_T scores to zero for any portion of the land use area that was classified built (urban/built-up), because such land has typically no biodiversity value. Third, we calculate the total STAR_T score for each power plant unit as the aggregated STAR_T score multiplied by the area of land-use footprint (in m^2). A higher value indicates that interventions to stop construction of a plant would contribute more to the mitigation of global extinction risk; in other words, larger values can be interpreted as reflecting more biodiversity-sensitive projects. As additional measures, we calculate for each plant the STAR_T density (STAR/m^2), calculated as the total STAR_T score divided by its footprint area (in m^2), and the STAR_T intensity (STAR/kW), calculated as the total STAR_T score divided by its capacity (in kilowatts). Figure IA I 8 illustrates the overlay between RE plants and the STAR_T map layer in Southeast Asia.

Given the complex nature of the STAR_T score, Table IA I 1 shows its correlation with the number of species that are affected by a RE plant, a simpler yet less precise

¹⁵Data on IUCN Red List of Threatened Species, Protected Area, and Key Biodiversity Area are also downloaded from IBAT, which are provided by BirdLife International, Conservation International, IUCN and UNEP-WCMC.

¹⁶Critically-endangered, endangered, vulnerable, or near-threatened species receive scores from 400 down to 100, respectively, while Least Concern species receive a score of zero. If a $5 \times 5 \text{ km}^2$ pixel contains, for example, 0.5% of a critically-endangered species’ global habitat ($0.005 \times 400 = 2$), 1% of a near-threatened species’ habitat ($0.01 \times 100 = 1$), and 5% of a least-concern species’ habitat ($0.05 \times 0 = 0$), the STAR_T value for that pixel would be 3.0 ($= 2 + 1 + 0$).

measure of biodiversity impact.¹⁷ The STAR_T score is highly positively correlated with the number of all affected species and the number of affected species that are classified as near threatened, vulnerable, endangered, and critically endangered. This corroborates that our STAR_T -based measure indeed captures impacts on species, especially critically-endangered ones.

III. Quantifying Biodiversity Impacts: Results

In this section, we use our newly constructed measure to quantify the biodiversity impacts of RE plants, both for plants individually and in aggregate. We then evaluate the biodiversity impacts by technology and over time. Lastly, we assess how concentrated these biodiversity impacts are across plants and owners.

A. Evidence on Overall Biodiversity Impacts

A.1. Current Biodiversity Impacts of RE Power Plants

[Table 2](#) quantifies the land-use-induced biodiversity impact of RE power plants, with statistics calculated at the power plant level. The average STAR_T score for a RE plant is about 129,910. Notably, the underlying distribution is highly skewed, with a 25th percentile value of 130, a median of 1,610, and a 75th percentile value of 13,850. Hence, the large average STAR_T score values are driven by a few plants with very large negative impacts on biodiversity.¹⁸ We also find that STAR_T scores per kW of capacity are highly skewed, with a mean value of 18.51 and a median of 0.13. The same holds for STAR_T scores per 1,000 m², with a mean value of 496.63 and a median of 11.50. Overall, the summary statistics indicate that the average plant is placed in an area with relatively low biodiversity value, while some plants are sited in locations that are very biodiversity-sensitive.¹⁹ When turning to a quantification by continent in [Table IA I 3](#), RE plants have the largest average biodiversity impacts in Africa (STAR_T score average of 366,040),

¹⁷For the table, we calculate the spatial intersection between each plant’s land-use footprint and IUCN species habitat maps. We then quantify the number of affected species per plant by IUCN Red List status (ranging from Least Concern to Critically Endangered).

¹⁸Because of this skewness, we use a log transformation in subsequent regressions. The log transformation is undefined for 237 observations for which the STAR_T score equals zero, which can be the case when the whole RE plant is on built-up land or on land with a STAR_T score of zero.

¹⁹Summary statistics on other variables are also in [Table 2](#). The average land use of RE plants is 0.52 km², which is again highly skewed. The total land use of all RE plants is about 21,300 km² ($40,911 \times 0.5210$), an area roughly equivalent to that of Slovenia or Israel. The average plant capacity 33.4 MW.

followed by the Americas and Asia/Oceania. On a per-m² basis, the biggest average effects are in Asia, Africa, and the Americas.

A.2. Expected Future Biodiversity Impacts of RE Power Plants

The total STAR_T score across all sampled RE plants is approximately five billion (40,911 times 129.91 times 1,000). This score is roughly equivalent to the biodiversity value of the entire forested area in Austria or the grass land in Thailand, and it exceeds the total biodiversity value of the land in Germany, Norway, or Poland.²⁰

With the expected growth of RE over the coming years, the total biodiversity impact of RE will become even more severe. According to IEA (2024), 5.5 TW of RE capacity will be added between 2024 and 2030, with solar accounting for 80 percent of this new capacity. Assuming that the biodiversity impact per MW remains constant and that hydro and wind contribute each 10 percent of the new capacity, the total STAR_T score of RE is expected to grow to nearly 50 billion by 2030. This number is equivalent to the biodiversity value of the entire land in Canada or Nepal.

A.3. RE Power Plants with the Largest Biodiversity Impacts

Table 3 provides a ranking of the ten power plant units with the largest land-use-induced biodiversity impacts, which includes six solar and three hydro units. The plant with the largest overall impact is the Five Wells Solar Center, a solar farm in Texas, United States, with a capacity of 342 MW and a STAR_T score of 327 million. The hydro plant with the largest STAR_T score is the El Cajon power plant in the Mexican state of Nayarit (in the sample as two units due to the two turbines employed), with a combined STAR_T score of about 120 million. An important insight emerging from the ranking is that some plants have very large biodiversity impacts despite relatively small overall capacities, for example the Romainville Solar Plant on the Seychelles with just 5 MW of capacity but a STAR_T score of 152 million.²² Conversely, some very large RE plants have only small

²⁰For comparison, Table IA I 2 lists the aggregate STAR_T scores (total and per m²) for the 30 countries with the largest number of RE plants in our sample. For each country, we tabulate the respective figures for all land types and separately for forested areas, grass land, and bare land. The top-3 countries with the highest STAR_T values are Indonesia, Mexico, and Brazil, while the largest value per m² occurs in Vietnam, Indonesia, and Mexico.²¹ Because we apply our m²-based STAR score to entire country in this table, the aggregate country-level numbers are large; a km² scale would make the numbers 1 million times smaller but would render the plant-level data impractically small. Therefore, the large country-level values are an artifact of applying our m² scale.

²²The high impact of this plant is due to its location in a globally significant biodiversity hotspot. The Seychelles hosts a large number of species for its size—more than most U.S. states or Chinese provinces.

biodiversity impacts, for example the Jinchang Jinchuan Solar Plant (capacity of 200 MW), which is located in a the Gobi desert (see [Figure IA I 11](#)). Hence, despite a large physical footprint, the presence in an ecosystem with low species richness implies that the STAR score can be small if the underlying land supports little wildlife.

A.4. Species Most Affected by RE Power Plants

We use spatial data associated with the IUCN Red List, specifically the mapped area of habitat, for over 127,000 species to directly assess the overlap between RE power plant footprints and the habitats of individual species. [Table 4](#) lists the species whose habitat areas are most affected. In Panel A, across the entire set of species, the top-10 most affected species are all classified as “least concern” according to the IUCN Red List, indicating low extinction risk.²³ Yet, Panels B and C show that many power plants are also built within the habitats of critically-endangered species. An example is the California Condor, for which 1,161 km² (or 0.98% of its habitat), overlap with RE plants. Two other affected species are the Asian White-backed Vulture or the Indian Black Vulture, both of which were common in the Indian subcontinent but are now critically endangered. [Figure IA I 9](#) visualizes the overlap between the area of habitat of the Indian Black Vulture and the locations of RE plants in South Asia.

B. Evidence on Biodiversity Impacts by Technology

Differences in biodiversity impacts across solar, wind, and hydro energy are important to understand, because each technology affects ecosystems in unique ways due to differences in land use and production locations. Understanding these differences allows RE planners, investors, and policymakers to choose appropriate sites, design effective mitigation measures, and balance RE development with ecosystem protection. Documenting and recognizing these variations is essential to ensure that RE contributes to both climate change mitigation and biodiversity conservation.

We quantify the biodiversity impact across technology types in [Figure 3](#). In Panel (a), which includes fossil-fuel and nuclear power plants as benchmarks, we aggregate the

These island species are often endemic with very small habitats, so any land use has a major impact. This specific plant’s location on a small, distinct island further elevates its biodiversity value. [Figure IA I 10](#) illustrates the location of the plant.

²³Most affected is the House Mouse, for which 20,469 km² of its area of habitat overlap with the land use of RE power plants. Since this species is widespread, this overlap accounts for only 0.05 percent of its total habitat.

STAR_T scores across all RE and non-RE plants and then allocate them to different technologies. Solar plants account for 46.9 percent of the total biodiversity impact, closely followed by hydro with 43.9 percent. Wind has a much smaller impact (7.6 percent). Non-RE plants also account for only 1.6 percent of the overall impact, primarily due to their limited land use.²⁴ When we exclude non-RE plants in Panel (b), solar accounts for 47.7 percent, hydro for 44.6 percent, and wind for 7.7 percent of the biodiversity impact within RE plants. Panel (c) plots the 25th percentile, median, and 75th percentile of the STAR_T score per plant by technology. In line with previous results, the median impact is highest for solar plants, followed by hydro and wind. For the 75th percentile, hydro is close to solar, indicating that the biodiversity impact of hydro plants is very skewed. The STAR_T scores for non-RE plants are low across all percentiles. Scaling the STAR_T score by capacity in Panel (d) confirms that solar has the highest biodiversity impact, followed by hydro, wind, and non-RE. With regard to land use per plant in Panel (e), solar plants require most space, followed by wind and hydro. Lastly, we analyze the biodiversity impact per 1,000 m² of land use in Panel (f). According to this metric, hydro plants are located in the most biodiversity-sensitive areas, followed by solar, non-RE plants, and wind. However, due to the lower land use of hydro plants, the overall biodiversity impact of solar plants is substantially higher (despite their less sensitive locations).

In Table 5, we complement the figures with regressions explaining the logarithm of the STAR_T score of a plant. The independent variables of interest are dummies that indicate whether a plant is a solar, wind, or hydro plant (fossil-fuel-based and nuclear plants are omitted to serve as the benchmark). Column (1) includes year fixed effects (based on the plant’s start of commercial operation) and location fixed effects. Location fixed effects are based on the country in which the plant is located or, for U.S. plants, based on the specific state.²⁵ These fixed effects ensure that we compare RE plants in the same location and year. We find that the STAR_T scores of solar plants are more than ten times ($= (\exp(2.7) - 1) \times 100$) higher than those of non-RE plants. For wind and hydro plants, STAR_T scores are approximately three times higher. When we include location-by-year fixed effects in Column (2), the results remain largely the same.

In Column (3), we additionally control for a plant’s land use so that we identify effects across technologies not from differences in land use, but only from locations in more or less biodiversity-sensitive areas. We find that hydro plants are located in areas that

²⁴Fossil-fuel-based power plants affect biodiversity primarily through the emissions they generate, which constitutes an impact dimension not reflected in this comparison.

²⁵Power plant regulation in the U.S.—different from most other countries—is generally implemented at the state level and about a quarter of all sampled plants are in the U.S.

are much more biodiversity sensitive compared to non-RE plants, with STAR_T scores that are five times higher than those of non-RE plants. Wind and solar plants are also located in more biodiversity-sensitive areas than non-RE plants, but the difference is less pronounced (around 15 to 20 percent). Controlling for the logarithm of a plant’s capacity in Column (4) does not materially change these estimates.

Overall, our results show that hydro plants are located in the most biodiversity-sensitive areas. When considering both plant size and location, solar plants are most detrimental to biodiversity.

C. Evidence on Biodiversity Impacts over Time

It is important to understand how the biodiversity impacts of RE plants evolved over time, to get insights into whether changes in technology, policy, or environmental awareness have improved the impact of RE. For example, it might be that early RE projects paid little attention to ecological consequences, while over time, as knowledge or monitoring increased, developers improved siting practices or introduced mitigation measures.

Different measures of the time-series biodiversity impact of RE plants are shown in [Figure 4](#). Panel (a) illustrates the total STAR_T score of all plants that started operation in a given year. The overall impact of RE plants increased six-fold over time, from a total STAR_T score of around 100 million in the early 2000s to 600 million in 2023. Notably, Panel (b) shows that also the median STAR_T score per plant increased over time, from around 200 per plant to nearly 8,000. When we scale the STAR_T score by plant capacity in Panel (c), we continue to find an increasing trend (though the STAR_T score per kW is relatively constant in the last few years). In terms of land use per plant, we detect a constant increase in Panel (d), from a median of less than 0.1 km² per plant in 2000 to approximately 0.7 km² in 2023. In terms of the STAR_T score per 1,000 m², Panel (e) shows that there is not much change over time. This indicates that the upward trend in the biodiversity impact of RE plants over time comes mostly from increased land use, not from more biodiversity-sensitive locations.

In [Table 6](#), Panel A, we complement these figures with regressions. We include location and technology fixed effects in Column (1) and location-by-technology fixed effects in the remaining columns. We confirm that the STAR_T score increased substantially over time, with a score increase of about three percent per year. When we control for a plant’s area and capacity in Columns (3) and (4), the estimate for the time trend decreases to roughly one-fifth of its previous magnitude. Thus, in line with [Figure 4](#), the increasing

biodiversity impact of RE plants is mainly driven by higher land use, though there is also some evidence that plants are constructed in more biodiversity-sensitive locations over time (as the time variable trend is still positive and significant in Columns (3) and (4)).

One potential reason why new RE plants are increasingly sited in more biodiversity-sensitive areas could be that there are fewer other options available, especially in regions that experienced a rapid RE expansion. Table 6, Panel B, considers this explanation by including as a control variable the share of the RE capacity in the total generation capacity of a country (or state in the U.S.) three years before the start of a plant's operation. Using location, technology, and year fixed effects in Column (1), we indeed find a higher biodiversity impact of new RE plants in locations where the existing RE share is higher. Adding year-times-technology fixed effects in Column (2) does not change this conclusion. When we control for a plant's area and capacity in Columns (3) and (4) to isolate effects due to locational choices from size effects, the coefficient estimate is reduced by approximately two-thirds, but it is still statistically significant. This specification implies that a one-percentage point increase in the RE capacity share is associated with a location of a new plant that has a 0.81 percent higher $STAR_T$ score.

Figure 5 shows the biodiversity impacts over time by technology. Panel (a) documents that hydro plants accounted for the vast majority of the biodiversity impact in the first half of the sample period. Solar overtook hydro in terms of impact in the mid-2010s, accounting for nearly of the total biodiversity impact as of today. Wind played a minor role in all years. For the median $STAR_T$ score per plant in Panel (b), we also find a sharp increase for solar (and at a lower level also for wind), while the impact of hydro remains relatively constant. When we scale the $STAR_T$ score by capacity in Panel (c), we find a slight increase in the biodiversity impact per unit of capacity for solar plants over time, while there are no clear trends for wind and hydro. With respect to land use, both solar and wind show an increasing time trend (with a more substantial increase for solar). For hydro plants, the land use is relatively constant. In terms of location, hydro plants are sited in the most biodiversity-sensitive areas during the entire sample period without clear time trends, as shown by the median $STAR_T$ score per 1,000 m² in Panel (e). For solar and wind plants, there is an upward trend in the impact per unit of land use. Hence, wind and solar plants are placed in more biodiversity-sensitive areas in recent years.

D. Evidence on Concentration of Biodiversity Impacts

It is important to understand whether the biodiversity impact of RE is concentrated among a small number of plants or is spread across many, because it determines how developers, investors, or policy makers can respond. If most of the impact is caused by a few specific plants, then targeted mitigation measures—such as adjusting siting or restoring local habitats—can address the issue. It would also allow restoration resources to be focused where they will have the greatest effect. However, if the impacts are widespread across many plants, it suggests a systemic problem that requires broader policy or planning changes (e.g., new siting standards or improved environmental assessments).

To address this question, we calculate in [Table 7](#), Panel A, the share of the overall $STAR_T$ score belonging to the top-10, top-100, and top-1,000 plants with the highest score; we also report for how much of the overall RE capacity these plants account. The results show that the 10 plants with the highest $STAR_T$ score account for 18.5 percent of the total $STAR_T$ score in our sample, but only provide 0.13 percent of the total capacity. The corresponding numbers for the top-100 (top-500) plants are 45.7 (71.8) percent for the $STAR_T$ score share and 0.7 (2.9) percent for the capacity share. When we consider the top-1% of plants, we find that they account for 68.9 percent of the total $STAR_T$ score, but only 2.5 percent of the total capacity (also reported in Panel A). The corresponding figures for the top-5% (top-10%) percent are 88.7 (94.6) percent for the $STAR_T$ score share and 10.9 (21.2) percent for the capacity share. These findings show that a very limited number of plants account for the vast majority of the biodiversity impact of RE, which is in line with the skewed distribution of the $STAR_T$ score in [Table 2](#). This high level of concentration implies that the biodiversity impact of RE plants could have been substantially reduced if the worst projects would not have been constructed. It also suggests that restoration resources should be focused to have the greatest overall effect.

In [Table 7](#), Panel B, we report the concentration of the biodiversity impact among the direct owners—reflecting the lowest-level identified owner in the ownership chain—of RE plants. The top-10 direct owners with the highest $STAR_T$ score account for 22.5 percent of the total biodiversity impact, but only 0.8 percent of the total capacity. The corresponding numbers for the top-100 (top-500) owners are 60.5 (86.3) percent $STAR_T$ score share and 9.6 (36.1) percent capacity share. When we focus on the top-1% (top-5%, top-10%) of owners with the highest impact, they account for 65.3 (89.2, 95.4) percent of the $STAR_T$ score and 11.4 (40.6, 55.9) percent of the capacity. The corresponding numbers for ultimate owners—the highest-level parent entity that controls the entire

ownership chain—in Table 7, Panel C, are slightly higher. This result implies that the negative biodiversity impact of RE is driven by a limited number of owners, although the concentration difference between the $STAR_T$ score and capacity share is somewhat less pronounced for owners compared to plant units. We examine the role of differences in ownership structure in more detail in the next section.

IV. Corporate Finance Applications

In this section, we provide three applications to illustrate how our measures of the biodiversity impacts of RE plants can be applied in a finance context to better understand the economics behind biodiversity loss. The first two applications focus on equity financing (the role of ownership), and the third application considers debt financing.

A. Publicly-listed versus Private Owners

In the first application, we analyze how RE plants owned by publicly-listed or private entities differ in the biodiversity impacts of their siting decisions. Our distinction between publicly-listed and private owners is motivated by earlier evidence that this ownership dimension relates to environmental externalities created by business activities. Specifically, Shive and Forster (2020) document that private firms are less likely to pollute, or to incur penalties from violating environmental regulations, compared to public firms. They attribute this effect to governance and incentive differences: private firms often have more concentrated ownership and direct accountability, which makes their owners more sensitive to reputational and long-term considerations. Publicly-listed firms, to the contrary, tend to face stronger short-term pressures that can encourage cost-consideration at the expense of environmental outcomes.²⁶ Applied to our setting, this evidence suggests that private owners should select locations for their RE plants that are associated with a lower biodiversity impact compared to that of publicly-listed owners.

To classify ownership into private or publicly-listed, we rely on S&P MI, which contains information about the names of the direct and ultimate owners of RE power plant units as well as their ownership stakes. We measure ownership three years before the start of commercial operation, because this typically corresponds to the moment when siting and construction-related decisions are made. Our variable of interest is *Listed*,

²⁶Shive and Forster (2020) also show that within publicly-listed firms, governance features that increase oversight are associated with better environmental performance, supporting the idea that accountability reduces externalities.

which equals one if either the direct or ultimate owner of a power plant unit is listed at a public exchange, and zero otherwise.²⁷

We test the prediction of our first application using the regressions reported in [Table 8](#). In these regressions, if a plant unit has multiple owners, we assign its biodiversity impact and production capacity to each owner according to the ownership share. We therefore consider each plant-unit owner combination as one observation (as a result, the number of observations is higher compared to the previous regressions). Either the direct or ultimate owners are publicly listed in 35.3 percent of RE plant units (17.5 percent of direct owners are publicly listed; the corresponding figure for ultimate owners is 32.5 percent). We identify ownership effects after including either technology-by-year and location-by-year fixed effects or technology-by-year-by-location fixed effects. These sets of fixed effects ensure that we compare publicly-listed and private firms within the same location for the same technology in a given year. This is important as not all technologies are suitable for all locations (e.g., hydro plants require very specific geological conditions) and some locations have higher overall biodiversity values than others (e.g., a high concentration of publicly-listed firms in regions with high biodiversity value would create positive correlations between listing status and biodiversity impacts). In Columns (1) and (2), we include only the indicator for whether an owner is a publicly-listed firm as well as technology-by-year and location-by-year or technology-by-location-by-year fixed effects. In Columns (3) and (4), we then additionally add as control variables the size of the power plants units and the associated capacity.

In Columns (1) and (2), publicly-listed owners are associated with a two-thirds higher biodiversity impact of their RE plants. When we add controls for the size of the power plants and capacity in Columns (3) and (4), the effect size decreases to a slightly less than 10 percent difference between the two owner types. Thus, capacity and land use differences between plants owned by public and private entities explain part of the difference, but not all of it. To conclude, RE plants owned by publicly-listed entities are sited in location where they have a higher biodiversity impact than those held by private entities. This effect arises because they are larger and placed in more biodiversity-sensitive areas.

²⁷While S&P MI contains information about the listing status of an owner, we additionally rely on an external ticker file (Compustat Global Link table) and manual research to deal with incomplete listing information. A challenge is that a firm's listing status can change over time; we classify a firm's listing status based on the most recent information. In cases where a subsidiary is listed but its parent company is not (or vice-versa), only the directly listed entity is classified as public.

B. *Financial versus Non-Financial Owners*

In the second application, we analyze how specific ownership types are correlated with the biodiversity impact of a power plant. In particular, we are interested in contrasting financial and non-financial owners. This separation is motivated by prior literature emphasizing that financial institutions face relatively more ESG-related pressures. Specifically, the actions of financial owners are shaped by a complex mix of financial, reputational, and normative pressures. While they are driven by financial motives to reduce portfolio-wide climate risk and mitigate financially material ESG concerns, they are also uniquely subject to non-financial pressures. These pressures stem from their clients' social preferences, their own moral/ethical considerations, and a strong desire to protect their reputations (Chen et al., 2020; Krueger et al., 2020). Furthermore, their sensitivity to ESG issues has been shown to be driven by the social norms of their home countries, which they transplant to the firms they invest in globally (Dyck et al., 2019). We predict that these distinct pressures—driven by client demands, reputational risk, and social norms—make financial owners particularly sensitive to considering biodiversity loss when deciding on the locations of RE plants they own.

We rely again on ownership information from S&P MI for our ownership classification. Our variable of interest is now *Financial Owner*, which equals one if the owner of a plant is one of the following institutions: bank, endowment fund, hedge fund, insurance company, mutual fund, PE fund, or pension fund. As in the previous application, to deal with multiple owners in the same plant unit, we consider each plant-unit-owner combination as one observation. In our sample, for 12.1 percent of plant-unit-owner links, there is a financial owner (23.8 percent of all plant units have at least one financial owner).²⁸

We test the prediction of our second application in Table 9, using the same fixed effects structures as before. We also estimate effects again at the plant-unit-owner level. In Columns (1) and (2), we include again only technology-by-year and location-by-year or technology-by-location-by-year fixed effects, but no control variables. We find that financial owners select locations for their RE plants that have a substantially lower biodiversity impact compared to those owned by non-financial owners. Once we control for the area of the power plant and its capacity in Columns (3) and (4), the difference shrinks in magnitude, but remains statistically significant. In these specifications, financial owners are associated with a decrease in the $STAR_T$ score of approximately 10 percent. These results imply that RE plants owned by financial investors are placed in areas where they

²⁸Table IA I 4 provides an overview on the classifications of the owners of the RE plant units.

have a lower biodiversity impact, because they tend to be smaller and because they are located in less biodiversity-sensitive areas.

C. Project Finance versus Corporate Finance

In the last application, we explore differences between RE plants that are project financed (off-balance sheet) versus those that are corporate financed (on-balance sheet). Project-financed plants are constructed in a separate company, typically a Special Purpose Vehicle (SPV). For plants financed through corporate finance, the investment is financed from the balance sheet of a parent company, without ring-fencing and separation through a SPV. The investment horizon of investors in the SPV is usually relatively long, as the repayment and dividend distribution only comes from the project cash flows over time (Esty, 2004). Moreover, in project finance, investors increasingly require an environmental (and social) due diligence, including biodiversity assessments or independent impact studies, which can even be formalized as covenants (Berg et al., 2024).²⁹ As a result, some project may not proceed if biodiversity safeguards are not met. Because an SPV is ring-fenced, any environmental non-compliance directly threatens the viability of the vehicle, creating strong incentives for responsible site selection and adherence to biodiversity standards. By contrast, corporate financing relies on internal capital and does not automatically trigger external environmental scrutiny. Large firms can more easily absorb environmental risks, fines, or delays, which reduces the pressure to minimize biodiversity impacts. To distinguish plants that are project or corporate financed, we use the classification of Heiss and Schmid (2025), which is based on data from LSEG Infra 360 and S&P MI.³⁰ In total, 29.2 percent of all RE plant units are project financed and 70.8 percent are corporate financed.

Table 10 estimates the relationship between the financing type of a plant unit and its biodiversity impact. In Columns (1) and (2), project-financed plants are located in areas where they have a lower biodiversity impact than those that are corporate financed, after including technology-by-year and location-by-year fixed effects or technology-by-location-by-year fixed effects. This effect is confirmed once we control for plant size and capacity in Columns (3) to (4). According to these specifications, the biodiversity impacts of

²⁹For example, banks following the Equator Principles require SPVs to meet biodiversity standards before receiving financing.

³⁰Since the coverage of the LSEG Infra 360 database is limited for smaller power plants, this classification is only for power plant units with at least 10 MW of capacity (approximately half of our sample).

project-financed RE plants are approximately 10 percent lower than those of corporate-financed RE plants, implying that project-financed plants have a lower impact mostly because they are placed in less biodiversity-sensitive areas.

V. Conclusion

The transition towards RE is the central pillar of climate change mitigation. However, pursuing these investments may involve environmental costs because RE plants can negatively affect biodiversity. These links indicate that mitigating climate change and biodiversity loss are closely intertwined. At this stage, however, large-scale, comprehensive evidence on the biodiversity impact of RE is lacking. We make progress towards closing this gap by constructing a novel global measure of the land-use-induced biodiversity impact of RE power plants, combining granular power plant location, remote sensing, and biodiversity data.

Our quantification shows that the RE plants in our sample generate a biodiversity impact, quantified as the aggregate $STAR_T$ score across all plants, equivalent to the value of the entire forested area in Austria or the grass land in Thailand. We estimate that the projected biodiversity impacts of RE could reach the scale of Canada’s total land biodiversity. Our approach is therefore not only relevant in quantifying the biodiversity impact of existing RE projects, but can also be used when evaluating future projects. We find that solar plants cause the greatest negative impact overall, while hydro plants are located in the most biodiversity-sensitive areas. The biodiversity impact of RE has grown substantially over time, driven by increased land use and siting in more biodiversity-sensitive locations. This impact is highly concentrated, with the top 1% of plants and owners being responsible for the majority of the biodiversity effects.

We apply our granular, location-based biodiversity measure to three finance-related settings to highlight factors associated with the biodiversity impact of RE plants. Across these applications, we find systematic differences in how project ownership and financing affect biodiversity through siting decisions. First, publicly-listed firms tend to develop larger plants in more sensitive areas, generating biodiversity impacts up to two-thirds higher than privately held firms, with a persistent gap even after controlling for the size of RE plants. Second, financial owners, who face pronounced ESG pressures, are associated with roughly 10 percent lower biodiversity impacts, partly due to locating projects in less sensitive areas. Third, project-financed plants—typically developed through SPVs—exhibit about 10 percent lower impacts than corporate-financed plants, reflecting siting

choices that avoid high-biodiversity areas. Together, these patterns show how ownership and financing structures correlate with biodiversity outcomes and demonstrate the value of fine-grained spatial data for biodiversity finance research.

Appendix

Appendix A: Definition of Variables

Variable	Description
$STAR_T$	Aggregated threat abatement score value of the STAR metric within a plant unit’s footprint on natural land. The STAR metric is a spatially explicit framework that quantifies the potential contribution of threat mitigation actions toward reducing global species extinction risk (Mair et al., 2021). Source: Integrated Biodiversity Assessment Tool (IBAT).
Area [m ²]	Area occupied by the power plant unit in square meters. Source: Own calculation based on remote sensing data (for all hydro plants and solar plants above 10 MW), approximation based on capacity and turbine type (for wind plants), or a log-linear regression model calibrated on the results from the remote sensing analysis of solar farms with more than 10 MW (for solar plants below 10 MW).
Land Type	The land types that we distinguish are trees (forest), grass (grassland/shrubland), built (urban/built-up), bare (bare ground), crops (cropland), snow/ice, and water. Source: GLAD Global Land Cover and Land Use Change (LCLUC) dataset (Potapov et al., 2022) until 2020 and Dynamic World Project (Brown et al., 2022) from 2021.
Capacity [MW] Share $RE_{location}^{t-3}$	Capacity of a power plant unit in MW. Source: S&P Market Intelligence. Renewable power plant capacity relative to the total electricity-generating capacity in the country where the power plant unit is located. The variable is measured three years before a plant unit’s start of commercial operation (which is approximately when the siting and other construction-related decision were made). Source: Own calculation based on S&P Market Intelligence.
Listing	Dummy variable that equals one if either a direct or ultimate owner of the power plant unit is listed at a public exchange, and zero otherwise. Source: Own classification that is based on S&P Market Intelligence.
Financial Owner	Dummy variable that equals one if either a direct or ultimate owner of a power plant unit is classified as a bank, endowment fund, hedge fund, insurance company, mutual fund, PE fund, or pension fund, and zero otherwise. Source: Own classification that is partly based on S&P Market Intelligence.
Project Financed	Dummy variable that equals one if a power plant unit is project financed (off-balance sheet), and zero if it is corporate financed (on-balance sheet). This classification is only available for power plant units with a capacity of more than 10 MW because the coverage of smaller units in the LSEG Infra 360 database is limited. Source: Classification from Heiss and Schmid (2025) based on S&P Market Intelligence and LSEG Infra 360.
Year COD	Year in which commercial operation started. Source: S&P Market Intelligence.

This table defines all key variables and lists the respective sources.

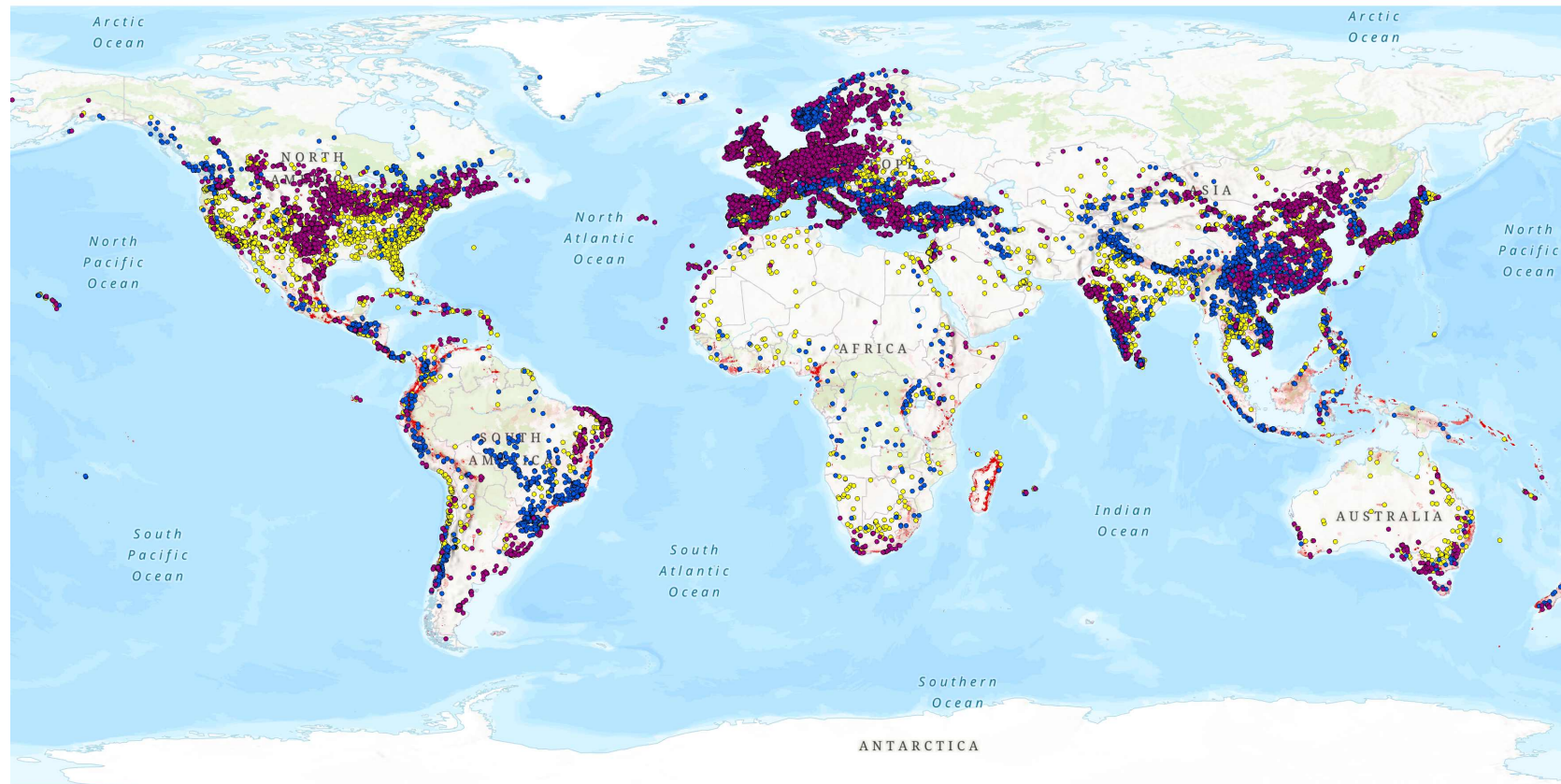
References

- APPA, 2025, America’s electricity generating capacity, Technical report, American Public Power Association.
- Asefa, Addisu, Yilma Dellelegn Abebe, Abdeta Debella Robi, Melesse Maryo, Gemedo Dalle, Kumara Wakjira, Antonin Vergez, Florence Curet, and Mekbebe Tessema, 2025, Validating application of the species threat abatement and restoration (STAR) metric in meeting national biodiversity conservation targets, *Biodiversity and Conservation* 34, 2715–2738.
- Berg, Tobias, Robin Döttling, Xander Hut, and Wolf Wagner, 2024, Do voluntary initiatives make loans greener? Evidence from project finance, Working Paper.
- Bridges, Amelia E. H., and Kerry L. Howell, 2025, Prioritisation of ocean biodiversity data collection to deliver a sustainable ocean, *Communications Earth & Environment* 6, 473.
- Brown, Christopher F., Steven P. Brumby, Brookie Gunder-Williams, Tanya Birch, Samantha Brooks Hyde, Joseph Mazzariello, Wanda Czerwinski, Valerie J Pasquarella, Robert Haertel, Simon Ilyushchenko, et al., 2022, Dynamic world, near real-time global 10 m land use land cover mapping, *Scientific Data* 9, 251.
- Chaudhary, Abhishek, Francesca Veronesi, Laura De Baan, and Stefanie Hellweg, 2015, Quantifying land use impacts on biodiversity: combining species–area models and vulnerability indicators, *Environmental science & technology* 49, 9987–9995.
- Chen, Fukang, Minhao Chen, Lin William Cong, Haoyu Gao, and Jacopo Ponticelli, 2025, Pricing the priceless: The financing cost of biodiversity conservation, Working Paper.
- Chen, Tao, Hui Dong, and Chen Lin, 2020, Institutional shareholders and corporate social responsibility, *Journal of Financial Economics* 135, 483–504.
- Cryan, Paul M., P. Marcos Gorresen, Cris D. Hein, Michael R. Schirmacher, Robert H. Diehl, Manuela M. Huso, David T.S. Hayman, Paul D. Fricker, Frank J. Bonaccorso, Douglas H. Johnson, et al., 2014, Behavior of bats at wind turbines, *Proceedings of the National Academy of Sciences* 111, 15126–15131.
- De Palma, Adriana, Andrew Hoskins, Ricardo E Gonzalez, Luca Börger, Tim Newbold, Katia Sanchez-Ortiz, Simon Ferrier, and Andy Purvis, 2021, Annual changes in the biodiversity intactness index in tropical and subtropical forest biomes, 2001–2012, *Scientific Reports* 11, 20249.
- Denholm, P., M. Hand, M. Jackson, and S. Ong, 2009, Land use requirements of modern wind power plants in the United States, National Renewable Energy Lab.
- Dionisio, D, P Audebert, L-S Schiettecatte, I Brierley, C Tribalet, and M Bernoux, 2023, *Technical guide for the Adaptation, Biodiversity and Carbon Mapping Tool: ABC-Map* (Food & Agriculture Org.).

- Durán, América P, Jonathan MH Green, Christopher D West, Piero Visconti, Neil D Burgess, Malika Virah-Sawmy, and Andrew Balmford, 2020, A practical approach to measuring the biodiversity impacts of land conversion, *Methods in Ecology and Evolution* 11, 910–921.
- Dyck, Alexander, Karl V. Lins, Lukas Roth, and Hannes F. Wagner, 2019, Do institutional investors drive corporate social responsibility? International evidence, *Journal of Financial Economics* 131, 693–714.
- Esty, Benjamin C., 2004, Why study large projects? An introduction to research on project finance, *European Financial Management* 10, 213–224.
- Flammer, Caroline, Thomas Giroux, and Geoffrey M. Heal, 2025, Biodiversity finance, *Journal of Financial Economics* 164, 103987.
- Frank, Eyal, and Anant Sudarshan, 2024, The social costs of keystone species collapse: Evidence from the decline of vultures in India, *American Economic Review* 114, 3007–3040.
- Garel, Alexandre, Arthur Romec, Zacharias Sautner, and Alexander F. Wagner, 2024, Do investors care about biodiversity?, *Review of Finance* 28, 1151–1186.
- Gasparatos, Alexandros, Christopher NH Doll, Miguel Esteban, Abubakari Ahmed, and Tabitha A Olang, 2017, Renewable energy and biodiversity: Implications for transitioning to a green economy, *Renewable and Sustainable Energy Reviews* 70, 161–184.
- Giglio, Stefano, Theresa Kuchler, Johannes Stroebel, and Oliver Wang, 2026, Nature and biodiversity loss: A research agenda for financial economics, *Journal of Finance: Insights and Perspectives*, forthcoming.
- Giglio, Stefano, Theresa Kuchler, Johannes Stroebel, and Xuran Zeng, 2025, Biodiversity risk, *Review of Finance* forthcoming.
- Heiss, Alexander, and Thomas Schmid, 2025, Project finance revisited, Working Paper.
- Hernandez, Rebecca R., Madison K. Hoffacker, Michelle L. Murphy-Mariscal, Grace C. Wu, and Michael F. Allen, 2015, Solar energy development impacts on land cover change and protected areas, *Proceedings of the National Academy of Sciences* 112, 13579–13584.
- Hertwich, Edgar G., Thomas Gibon, Evert A. Bouman, Anders Arvesen, Sangwon Suh, Garvin A. Heath, Joseph D. Bergesen, Andrea Ramirez, Mabel I. Vega, and Lei Shi, 2015, Integrated life-cycle assessment of electricity-supply scenarios confirms global environmental benefit of low-carbon technologies, *Proceedings of the National Academy of Sciences* 112, 6277–6282.
- IEA, 2024, Renewables 2024: Analysis and forecasts to 2030, Technical report, International Energy Agency.
- IREA, 2025, Delivering on the UAE consensus: Tracking progress toward tripling renewable energy capacity and doubling energy efficiency by 2025, Technical report, International Renewable Energy Agency.

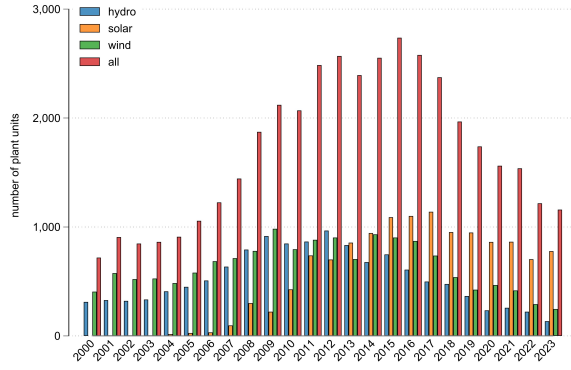
- Jenkins, Clinton N, Stuart L Pimm, and Lucas N Joppa, 2013, Global patterns of terrestrial vertebrate diversity and conservation, *Proceedings of the National Academy of Sciences* 110, E2602–E2610.
- Krueger, Philipp, Zacharias Sautner, and Laura T Starks, 2020, The importance of climate risks for institutional investors, *Review of Financial Studies* 33, 1067–1111.
- Kruitwagen, Lucas, K.T. Story, J. Friedrich, L. Byers, S. Skillman, and Cameron Hepburn, 2021, A global inventory of photovoltaic solar energy generating units, *Nature* 598, 604–610.
- Lammerant, Johan, Kim Driesen, Jolien Verhelst, and Jo De Ryck, 2022, Assessment of biodiversity measurement approaches for businesses and financial institutions – update 4, Technical report, EU Business @ Biodiversity Platform, Brussels.
- Li, Xuecao, Peng Gong, Yuyu Zhou, Jie Wang, Yuqi Bai, Bin Chen, Tengyun Hu, Yixiong Xiao, Bing Xu, Jun Yang, et al., 2020, Mapping global urban boundaries from the global artificial impervious area (GAIA) data, *Environmental Research Letters* 15, 094044.
- Lopez, Anthony, Trieu Mai, Eric Lantz, Dylan Harrison-Atlas, Travis Williams, and Galen Maclaurin, 2021, Land use and turbine technology influences on wind potential in the United States, *Energy* 223, 120044.
- Luderer, Gunnar, Michaja Pehl, Anders Arvesen, Thomas Gibon, Benjamin L Bodirsky, Harmen Sytze De Boer, Oliver Fricko, Mohamad Hejazi, Florian Humpenöder, Gokul Iyer, et al., 2019, Environmental co-benefits and adverse side-effects of alternative power sector decarbonization strategies, *Nature Communications* 10, 5229.
- Mair, Louise, Eduardo Amorim, Monira Bicalho, Thomas M. Brooks, Vincente Calfo, Renata de T. Capellão, Colin Clubbe, Marianne Evju, Eduardo P. Fernandez, Gláucia C Ferreira, et al., 2023, Quantifying and mapping species threat abatement opportunities to support national target setting, *Conservation Biology* 37, e14046.
- Mair, Louise, Leon A. Bennun, Thomas M. Brooks, Stuart H.M. Butchart, Friederike C. Bolam, Neil D. Burgess, Jonathan M.M. Ekstrom, E.J. Milner-Gulland, Michael Hoffmann, Keping Ma, et al., 2021, A metric for spatially explicit contributions to science-based species targets, *Nature Ecology & Evolution* 5, 836–844.
- Meng, Lina, Pengfei Liu, Yinggang Zhou, and Yingdan Mei, 2025, Blaming the wind? The impact of wind turbine on bird biodiversity, *Journal of Development Economics* 172, 103402.
- Montesino Pouzols, Federico, Tuuli Toivonen, Enrico Di Minin, Aija S Kukkala, Peter Kullberg, Johanna Kuusterä, Joonas Lehtomäki, Henriikki Tenkanen, Peter H Verburg, and Atte Moilanen, 2014, Global protected area expansion is compromised by projected land-use and parochialism, *Nature* 516, 383–386.
- NextEnergy, 2025, Nature strategy & delivery framework, Technical report, NextEnergy Group.

- Nvidia, 2025, Sustainability report: Fiscal year 2025, <https://images.nvidia.com/aem-dam/Solutions/documents/NVIDIA-Sustainability-Report-Fiscal-Year-2025.pdf>.
- Pekel, Jean-François, Andrew Cottam, Noel Gorelick, and Alan S. Belward, 2016, High-resolution mapping of global surface water and its long-term changes, *Nature* 540, 418–422.
- Potapov, Peter, Matthew C Hansen, Amy Pickens, Andres Hernandez-Serna, Alexandra Tyukavina, Svetlana Turubanova, Viviana Zalles, Xinyuan Li, Ahmad Khan, Fred Stolle, et al., 2022, The global 2000–2020 land cover and land use change dataset derived from the landsat archive: first results, *Frontiers in Remote Sensing* 3, 856903.
- Schipper, Aafke M, Jelle P Hilbers, Johan R Meijer, Laura H Antão, Ana Benítez-López, Melinda MJ de Jonge, Luuk H Leemans, Eddy Scheper, Rob Alkemade, Jonathan C Doelman, et al., 2020, Projecting terrestrial biodiversity intactness with globio 4, *Global Change Biology* 26, 760–771.
- Schneider, Julia M, Ruth Delzeit, Christian Neumann, Tobias Heimann, Ralf Seppelt, Franziska Schuenemann, Mareike Söder, Wolfram Mauser, and Florian Zabel, 2024, Effects of profit-driven cropland expansion and conservation policies, *Nature Sustainability* 7, 1335–1347.
- Shive, Sophie A., and Margaret M. Forster, 2020, Corporate governance and pollution externalities of public and private firms, *Review of Financial Studies* 33, 1296–1330.
- Stroebe, Johannes, and Xuran Zeng, 2025, Biodiversity vs. climate risk exposures of renewable energy firms, Working Paper.
- Thaker, Maria, Amod Zambre, and Harshal Bhosale, 2018, Wind farms have cascading impacts on ecosystems across trophic levels, *Nature Ecology & Evolution* 2, 1854–1858.
- Visser, Elke, Vonica Perold, Samantha Ralston-Paton, Alvaro C Cardenal, and Peter G Ryan, 2019, Assessing the impacts of a utility-scale photovoltaic solar energy facility on birds in the Northern Cape, South Africa, *Renewable Energy* 133, 1285–1294.
- Wang, Jingyu, Cai Li, Zhongci Deng, Jamie Carr, Lindsay C Stringer, Keke Li, Yuanchao Hu, Chen Zeng, Kai Huang, Sha Peng, et al., 2025, Biodiversity impacts of land occupation for renewable energy infrastructure in a globally connected world, *Environmental Science & Technology* 59, 9529–9539.
- Zarfl, Christiane, Alexander E. Lumsdon, Jürgen Berlekamp, Laura Tydecks, and Klement Tockner, 2015, A global boom in hydropower dam construction, *Aquatic Sciences* 77, 161–170.

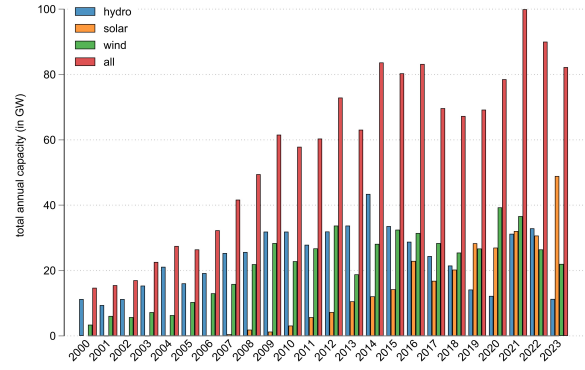


Esri, TomTom, FAO, NOAA, USGS, Esri, USGS

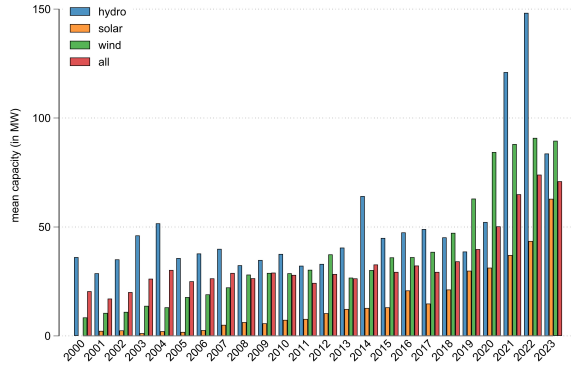
Figure 1: This figure shows the locations of solar plants (yellow), wind plants (purple), and hydro plants (blue) included in the sample. The plants became operational between 2000 and 2023 and meet the minimum capacity thresholds of 1 MW.



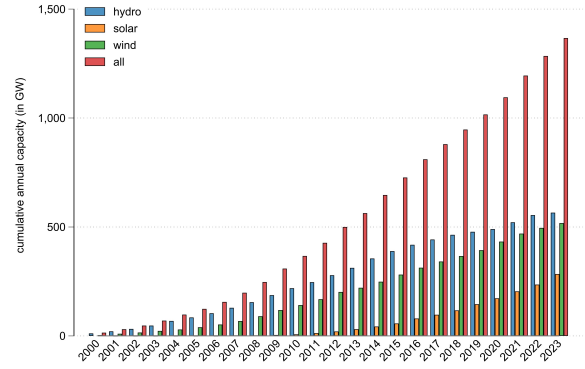
(a) Number of new plant units



(b) Total capacity of new plants

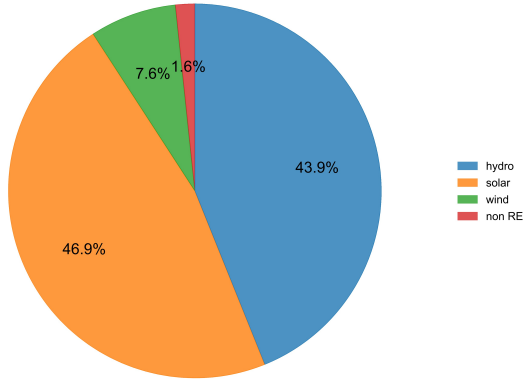


(c) Average capacity of new plants

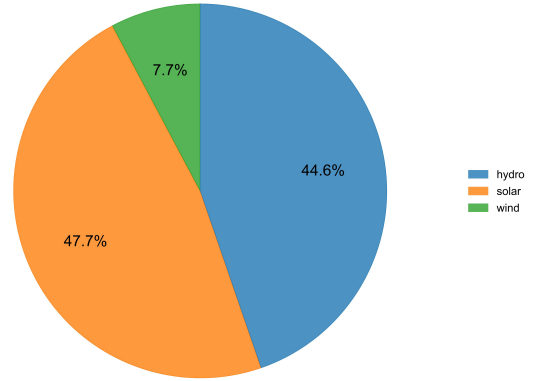


(d) Cumulative capacity

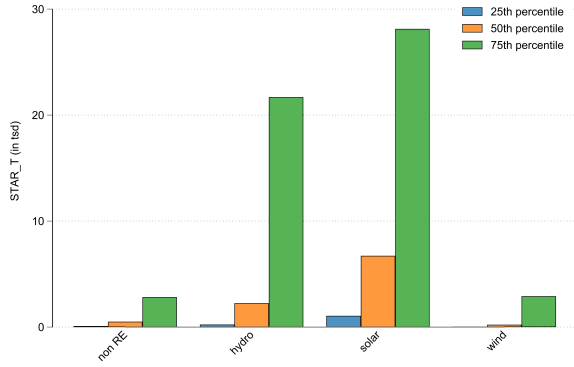
Figure 2: Panel (a) shows the number of new power plant units by technology and year. Panel (b) shows the total newly added capacity by year and technology and Panel (c) the average capacity of newly added plants by year and technology. Panel (d) shows the cumulative capacity by technology since 2000. Only power plant units included in our sample are considered.



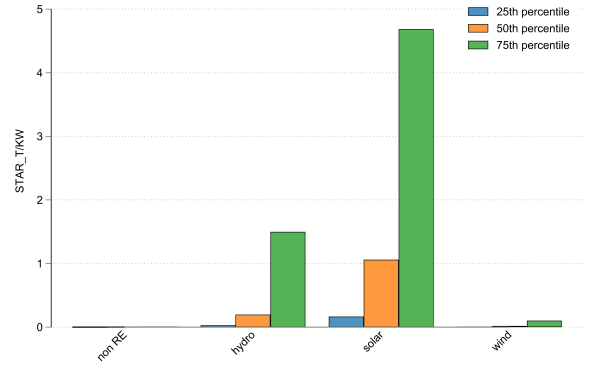
(a) Total $STAR_T$ score



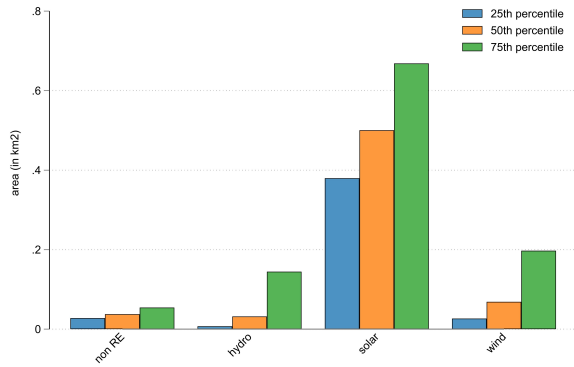
(b) Without non RE



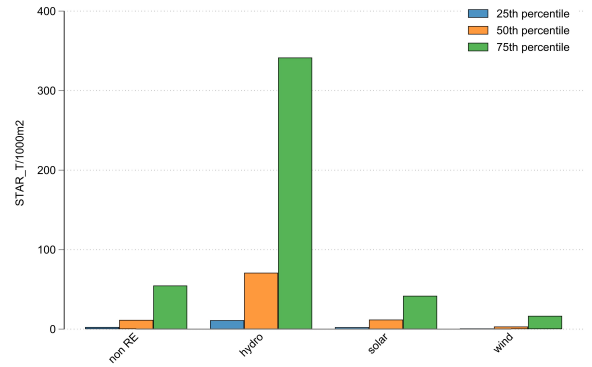
(c) $STAR_T$ per plant



(d) $STAR_T$ per kW

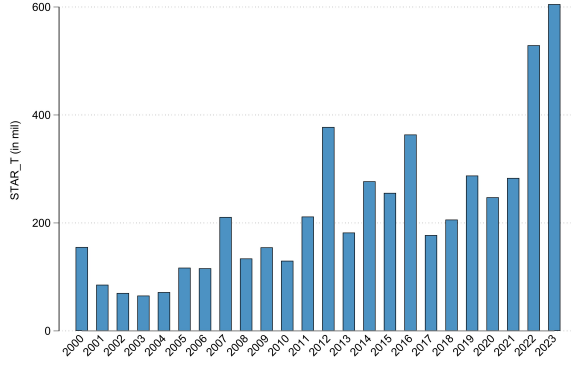


(e) Land use per plant in km^2

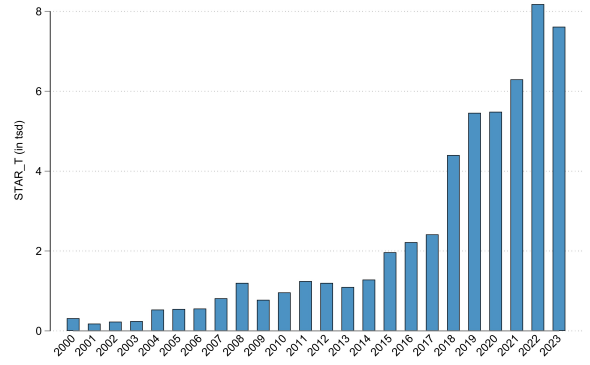


(f) $STAR_T$ per 1,000 m^2

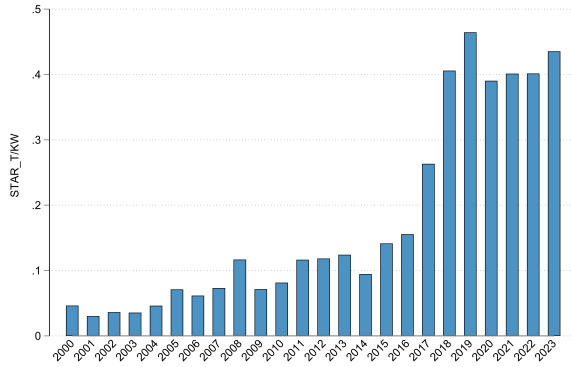
Figure 3: These figures show the land-use induced biodiversity impact of RE and non-RE plants by technology. Panels (a) and (b) show how much plant units with different technologies contribute to the total $STAR_T$ score (with and without non-RE plants). Panel (c) shows the 25th, 50th, and 75th percentile of the $STAR_T$ score in thousand per power plant unit. Panel (d) plots the $STAR_T$ score per KW of capacity. Panel (e) shows the land use in square kilometers and Panel (f) the $STAR_T$ score per 1,000 m^2 of land use.



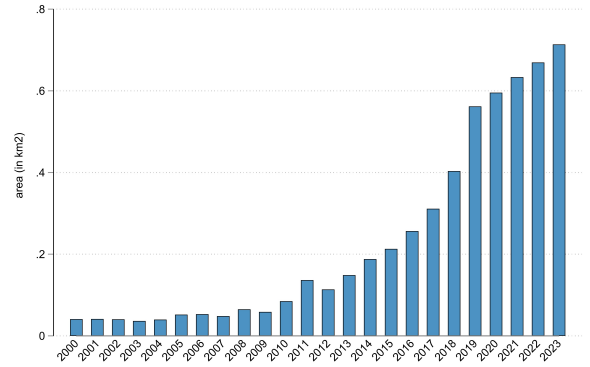
(a) Total $STAR_T$ score



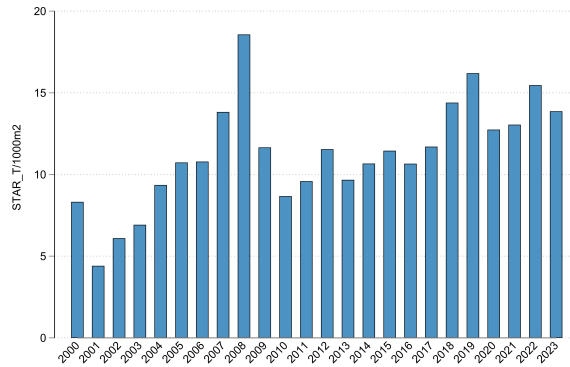
(b) $STAR_T$ per plant



(c) $STAR_T$ per kW



(d) Land use per plant in km^2



(e) $STAR_T$ per 1,000 m^2

Figure 4: These figures show the land-use induced biodiversity impact of renewable power plants over time. Panel (a) shows the total $STAR_T$ score. Panel (b) shows median $STAR_T$ score in thousand per power plant unit. Panel (c) plots the median $STAR_T$ score per kilowatt of capacity. Panel (d) shows the median land use in square kilometers and Panel (e) the median $STAR_T$ score per 1,000 m^2 of land use. Only power plant units included in our sample are considered for this illustration.

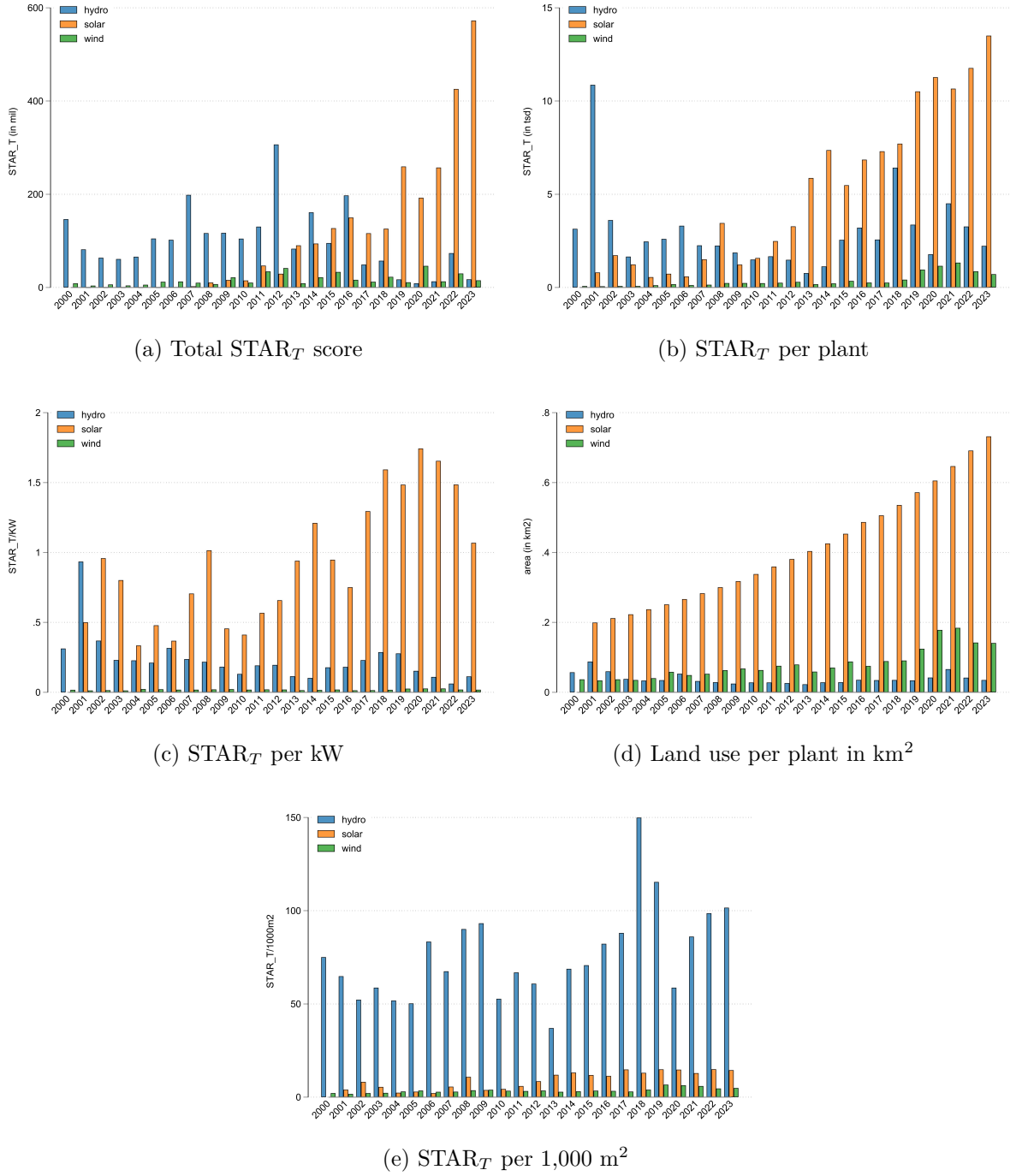


Figure 5: These figures show the land-use induced biodiversity impacts of renewable power plants over time. Panel (a) shows the total $STAR_T$ score. Panel (b) shows median $STAR_T$ score (in thousand) per power plant unit. Panel (c) plots the median $STAR_T$ score per kilowatt of capacity. Panel (d) shows the median land use in square kilometers, and Panel (e) the median $STAR_T$ score per 1,000 m^2 of land use. Only power plant units included in our sample are considered for this illustration.

Table 1: Evidence on Land Type Use

Land Type	Hydro	Wind	Solar	Total
Bare	6.9%	23.9%	10.9%	18.4%
Built	10.6%	20.4%	16.8%	17.8%
Crops	3.1%	12.3%	7.9%	9.7%
Grass	33.0%	25.6%	40.2%	29.1%
Snow/Ice	0.1%	0.0%	0.0%	0.0%
Trees	42.2%	16.1%	22.5%	22.7%
Water	4.2%	1.7%	1.7%	2.3%
Sum	100.0%	100.0%	100.0%	100.0%

This table illustrates the land use of RE plants, both separately for individual technologies and in total. The percentage indicate the proportion of the total area occupied by all RE plants—or those utilizing specific technologies—that is classified as a particular land type. Percentages are calculated based on the total land use of all RE plants in the sample. Variables definitions can be found in [Appendix A](#).

Table 2: Quantification of Biodiversity Impacts of RE Plants

Variable	Obs.	Mean	p25	p50	p75	SD
STAR_T [tsd]	40,911	129.91	0.13	1.61	13.85	2,231.69
STAR_T/kW	40,911	18.51	0.01	0.13	1.41	326.06
$\text{STAR}_T/1,000\text{m}^2$	40,911	496.63	2.27	11.50	75.35	3,766.51
Area [km^2]	40,911	0.52	0.03	0.15	0.47	1.80
Capacity [MW]	40,911	33.42	3.00	9.10	30.00	76.71

This table quantifies the biodiversity impact and presents descriptive statistics for other related variable of all RE plants. Variable definitions can be found in [Appendix A](#).

Table 3: Top 10 RE Power Plants with the Highest Biodiversity Impacts

Power Plant	Technology	Country	Year	Capacity	STAR _T [million]
Five Wells Solar Center	Solar	USA	2023	355.40	327.72
Mangilao Solar Plant	Solar	USA	2022	60.00	149.66
Romainville Solar Plant	Solar	Seychelles	2022	5.00	149.40
El Cajon 1	Hydro	Mexico	2007	375.00	59.96
El Cajon 2	Hydro	Mexico	2007	375.00	59.96
East Blackland Solar Project	Solar	USA	2021	144.00	55.90
Upper Kotmale Hydro Plant_1	Hydro	Sri Lanka	2012	75.00	46.19
Upper Kotmale Hydro Plant_2	Hydro	Sri Lanka	2012	75.00	46.19
Tuli Energia Solar PV	Solar	Mexico	2020	150.00	46.01
Metz Solar Plant	Solar	Australia	2022	115.00	44.32

This table shows the ten RE plants in our sample with the highest STAR_T score, sorted in descending order. The STAR_T score is reported in millions. Year is the year in which commercial operation started and capacity is measured in MW. Variable definitions can be found in [Appendix A](#).

Table 4: Individual Species Affected by RE Plants

Binomial nomenclature	English name	Status	Habitat km ²	Habitat %
Panel A: All Species				
<i>Mus musculus</i>	Eastern House Mouse	LC	20,469	0.05%
<i>Hirundo rustica</i>	Barn Swallow	LC	19,915	0.70%
<i>Pandion haliaetus</i>	Fish Hawk	LC	18,513	0.10%
<i>Ardea alba</i>	American Egret	LC	18,233	0.14%
<i>Falco peregrinus</i>	Duck Hawk	LC	17,507	0.08%
<i>Passer domesticus</i>	House Sparrow	LC	15,925	0.07%
<i>Tyto alba</i>	Barn Owl	LC	15,180	0.05%
<i>Bubulcus ibis</i>	Cattle Egret	LC	14,920	4.38%
<i>Asio flammeus</i>	Short-eared Owl	LC	14,227	0.20%
<i>Nycticorax nycticorax</i>	Black-crowned Night Heron	LC	13,990	0.18%
Panel B: Critically-Endangered Species				
<i>Aythya baeri</i>	Baer's Pochard	CR	2,585	0.08%
<i>Gyps bengalensis</i>	Asian White-backed Vulture	CR	2,298	0.08%
<i>Sarcogyps calvus</i>	Indian Black Vulture	CR	1,880	0.08%
<i>Vanellus gregarius</i>	Sociable Lapwing	CR	1,223	0.08%
<i>Emberiza aureola</i>	Yellow-breasted Bunting	CR	1,217	0.06%
<i>Gyps indicus</i>	Indian Griffon	CR	1,213	0.10%
<i>Gymnogyps californianus</i>	California Condor	CR	1,161	0.98%
<i>Mustela lutreola</i>	European Mink	CR	1,141	0.13%
<i>Campephilus principalis</i>	Ivory-billed Woodpecker	CR	908	0.11%
<i>Sypheotides indicus</i>	Lesser Florican	CR	904	0.15%

This table shows the species whose habitat area is most affected by renewable power plants. The first column shows the species name in binomial nomenclature, the second column shows the english name, and the third column the extinction risk status according to the IUCN Red List. The fourth column shows the habitat area in square kilometers that overlaps with the land use of the renewable power plants in our sample. The last column shows the affected habitat area scaled by the whole habitat of the species. Panel A considers all species and Panel B considers critically endangered species. LC stands for least concern, i.e., species that have a low extinction risk and CR for critically endangered. English species names are obtained from the Global Biodiversity Information Facility (GBIF).

Table 5: Biodiversity Impacts across Technologies

	Log STAR _T			
	(1)	(2)	(3)	(4)
Solar	2.70*** (43.6)	2.80*** (38.2)	0.14** (1.99)	0.14 (1.47)
Wind	1.00*** (16.5)	1.09*** (15.7)	0.17*** (2.70)	0.17** (2.26)
Hydro	1.34*** (19.3)	1.40*** (18.3)	1.73*** (26.1)	1.73*** (21.5)
Log Area [m ²]			0.99*** (94.0)	0.99*** (77.1)
Log Capacity [MW]				4.4e-06 (0.00031)
Observations	49,592	49,052	49,052	49,052
Adj. R ²	0.49	0.53	0.70	0.70
Location FE	Yes	n/a	n/a	n/a
Year FE	Yes	n/a	n/a	n/a
Location × Year FE	No	Yes	Yes	Yes

The dependent variable is the natural logarithm of the STAR_T score of a power plant unit. Solar, wind, and hydro are dummy variables that equal one for solar, wind, and hydro plants, respectively. Non-RE plants (i.e., fossil-fuel based and nuclear plants) are omitted and serve as the baseline category. Location fixed effects on the country or U.S. state in which the plant is located and year fixed-effects are based on the the plant's start year of commercial operation. *t*-statistics based on robust standard errors clustered by power plants are presented in parentheses. ***, ** and * indicate significance at the 1%-, 5%- and 10%-levels, respectively. Variables definitions can be found in [Appendix A](#).

Table 6: Biodiversity Impacts over Time

Panel A: Start Year of Commercial Operation				
	Log STAR _T			
	(1)	(2)	(3)	(4)
Year COD	0.027*** (7.43)	0.026*** (7.24)	0.0055** (2.15)	0.0064** (2.42)
Log Area [m ²]			0.98*** (99.8)	0.99*** (82.1)
Log Capacity [MW]				-0.017 (-1.26)
Observations	40,656	40,603	40,603	40,603
Adj. R ²	0.51	0.55	0.74	0.74
Location FE	Yes	n/a	n/a	n/a
Technology FE	Yes	n/a	n/a	n/a
Technology × Year FE	No	Yes	Yes	Yes
Panel B: RE Capacity Share				
	Log STAR _T			
	(1)	(2)	(3)	(4)
Share RE _{location} ^{t-3}	2.80*** (5.79)	2.11*** (3.93)	0.83** (2.48)	0.81** (2.41)
Log Area [m ²]			0.99*** (101)	1.00*** (86.0)
Log Capa [MW]				-0.017 (-1.30)
Observations	40,601	40,601	40,601	40,601
Adj. R ²	0.52	0.52	0.72	0.72
Location FE	Yes	Yes	Yes	Yes
Technology FE	Yes	n/a	n/a	n/a
Year FE	yes	n/a	n/a	n/a
Technology × Year FE	no	yes	yes	yes

continued on next page

Table 6 continued

The dependent variable is the natural logarithm of the $STAR_T$ score of a power plant unit in both Panels. In Panel A, the key independent variable is Year COD, which is defined as the year in which commercial operation started. In Panel B, the key independent variable is $Share\ RE_{location}^{t-3}$, which is defined as the share of RE production capacity relative to the total generation capacity at the location of the RE plant. This variable is measured three years before the start of commercial operation of the plant. Location fixed effects on the country or U.S. state in which the plant is located, technology fixed-effects are based on the the plant's generation technology (solar, wind, hydro), and year fixed effects are based on the the plant's start year of commercial operation. t -statistics based on robust standard errors clustered by power plants are presented in parentheses. ***, ** and * indicate significance at the 1%-, 5%- and 10%-levels, respectively. Variables definitions can be found in [Appendix A](#).

Table 7: Concentration of Biodiversity Impacts

	STAR _T	Capacity
Panel A: Plant Units		
Top-10 Plant Units	18.5%	0.1%
Top-100 Plant Units	45.7%	0.7%
Top-500 Plant Units	71.8%	2.9%
Top-1% Plant Units	68.9%	2.5%
Top-5% Plant Units	88.7%	10.9%
Top-10% Plant Units	94.6%	21.2%
Panel B: Direct Owners		
Top-10 Direct Owners	22.5%	0.8%
Top-100 Direct Owners	60.5%	9.6%
Top-500 Direct Owners	86.3%	36.1%
Top-1% Direct Owners	65.3%	11.4%
Top-5% Direct Owners	89.2%	40.6%
Top-10% Direct Owners	95.4%	55.9%
Panel C: Ultimate Owners		
Top-10 Ultimate Owners	23.9%	6.8%
Top-100 Ultimate Owners	65.2%	29.3%
Top-500 Ultimate Owners	89.5%	50.3%
Top-1% Ultimate Owners	67.5%	31.3%
Top-5% Ultimate Owners	90.7%	53.7%
Top-10% Ultimate Owners	96.2%	65.1%

This table shows in Panel A the share of the total STAR_T score and of the total RE capacity that is related to the top-10/top-100/top-500 power plant units or the top-1%/top-5%/top-10% of power plant units. Panel B and C provide corresponding statistics for direct owners or ultimate owners. Direct owners reflect the lowest-level identified owner in the ownership chain, while ultimate owners reflect the highest-level parent entity that controls the entire ownership chain.

Table 8: Publicly-Listed versus Private Ownership

	Log STAR _T			
	(1)	(2)	(3)	(4)
Listing	0.52*** (6.05)	0.52*** (6.13)	0.067** (2.31)	0.073** (2.50)
Log Area [m ²]			1.00*** (163)	1.02*** (87.9)
Log Capacity [MW]				-0.028** (-2.23)
Observations	64,069	64,024	64,024	64,024
Adj. R ²	0.46	0.50	0.80	0.80
Technology × Year FE	Yes	n/a	Yes	n/a
Location × Year FE	Yes	n/a	Yes	n/a
Technology × Location × Year FE	No	Yes	No	Yes

The dependent variable is the natural logarithm of the STAR_T score of a power plant unit. Listing equals one if either the direct or ultimate owner of the power plant unit is listed at a public exchange, and zero otherwise. Regressions are estimated at the plant-unit-owner level. *t*-statistics based on robust standard errors clustered by the plant units' ultimate parents are presented in parentheses. ***, ** and * indicate significance at the 1%-, 5%- and 10%-levels, respectively. Variable definitions can be found in [Appendix A](#).

Table 9: Financial versus Non-Financial Ownership

	Log STAR _T			
	(1)	(2)	(3)	(4)
Financial Owner	-0.68*** (-4.93)	-0.68*** (-5.02)	-0.082** (-2.48)	-0.086** (-2.56)
Log Area [m ²]			1.00*** (162)	1.02*** (87.3)
Log Capacity [MW]				-0.027** (-2.12)
Observations	63,835	63,792	63,792	63,792
Adj. R ²	0.46	0.50	0.80	0.80
Technology × Year FE	Yes	n/a	Yes	n/a
Location × Year FE	Yes	n/a	Yes	n/a
Technology × Location × Year FE	No	Yes	No	Yes

The dependent variable is the natural logarithm of the STAR_T score of a power plant unit. Financial owner equals one if either the direct or ultimate owner of the power plant unit is classified as bank, endowment fund, hedge fund, insurance company, mutual fund, PE fund, or pension fund, and zero otherwise. Regressions are estimated at the plant-unit-owner level. *t*-statistics based on robust standard errors clustered by the plant units' ultimate parents are presented in parentheses. ***, ** and * indicate significance at the 1%-, 5%- and 10%-levels, respectively. Variable definitions can be found in [Appendix A](#).

Table 10: Project versus Corporate Financing

	Log STAR _T			
	(1)	(2)	(3)	(4)
Project Financed	-0.16** (-2.41)	-0.19*** (-2.90)	-0.11*** (-3.29)	-0.10*** (-3.24)
Log Area [m ²]			1.00*** (131)	1.01*** (63.3)
Log Capacity [MW]				-0.0066 (-0.37)
Observations	41,792	41,768	41,768	41,768
Adj. R ²	0.42	0.46	0.79	0.79
Technology × Year FE	Yes	n/a	Yes	n/a
Location × Year FE	Yes	n/a	Yes	n/a
Technology × Location × Year FE	No	Yes	No	Yes

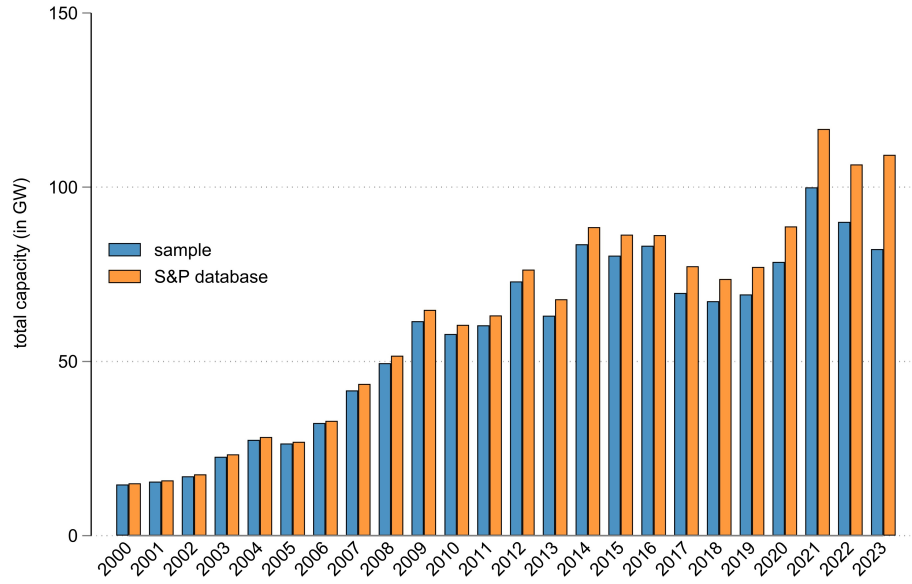
The dependent variable is the natural logarithm of the STAR_T score of a power plant unit. Only power plant units with a capacity of at least 10 MW are included in this analysis. Project Financed equals one if the power plant unit is project financed (off-balance sheet), and zero if it is corporate financed (on-balance sheet). Regressions are estimated at the plant-unit-owner level. *t*-statistics based on robust standard errors clustered by the plant units' ultimate parents are presented in parentheses. ***, ** and * indicate significance at the 1%-, 5%- and 10%-levels, respectively. Variable definitions can be found in [Appendix A](#).

Internet Appendix

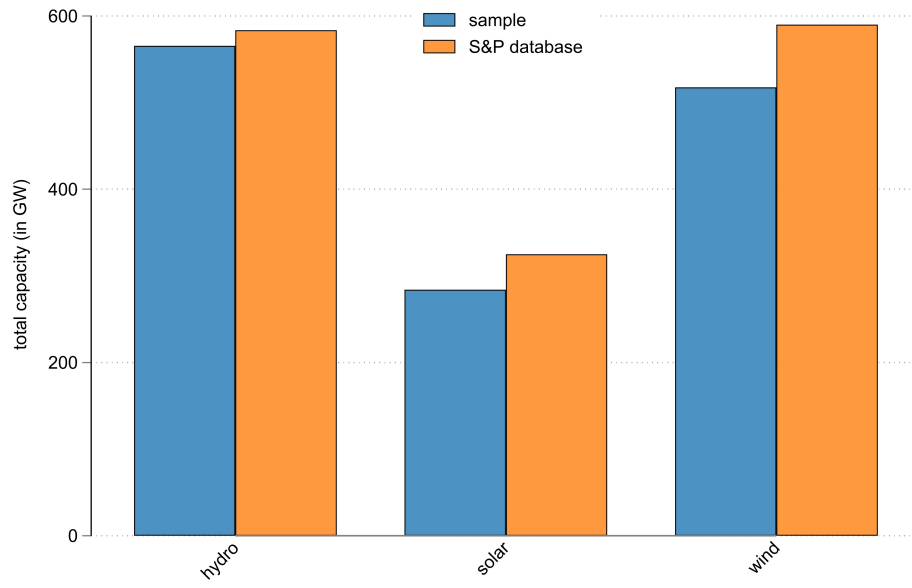
for

Biodiversity Impacts of Renewable Energy

Internet Appendix I: Additional Tables and Figures



(a) Comparison by year



(b) Comparison by technology

Figure IA I 1: This figures compares the RE capacity included in our sample with the RE capacity in S&P Market Intelligence. We report a comparison by year in Panel (a) and by technology in Panel (b).

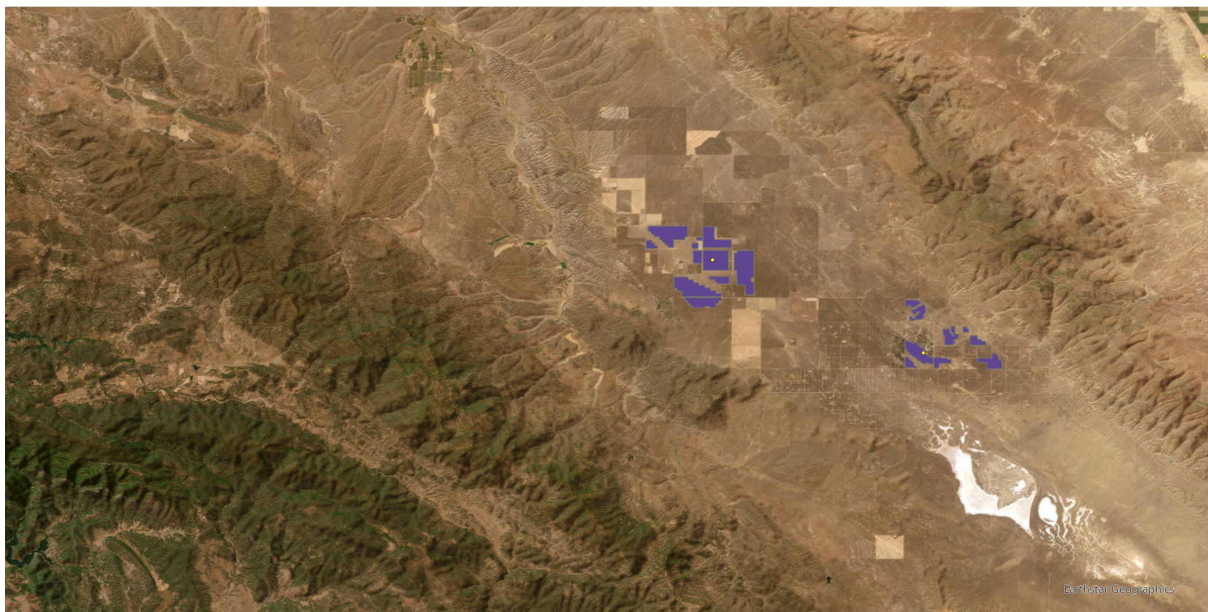


Figure IA I 2: These figures illustrate the identification of a solar plant footprint using Sentinel-2 satellite data. The plant is the Topaz Solar Farm in California, U.S., with a capacity of 129 MW. The top picture shows the original satellite image. The bottom picture illustrates the plant detection algorithm, with the area affected by the solar plant colored in purple.



Figure IA I 3: This figure shows the detected solar farm footprints near Königsberg, Germany. This example illustrates the methodology for handling clusters of plants, where total land use is calculated for closely-sited facilities and then allocated to individual plants based on their capacity.

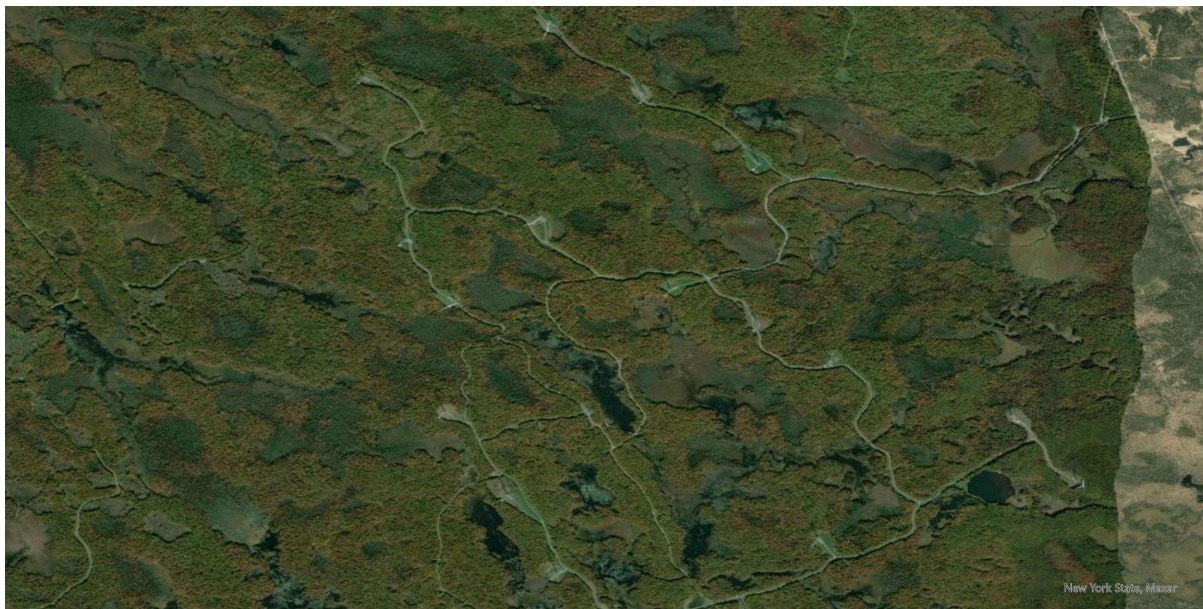


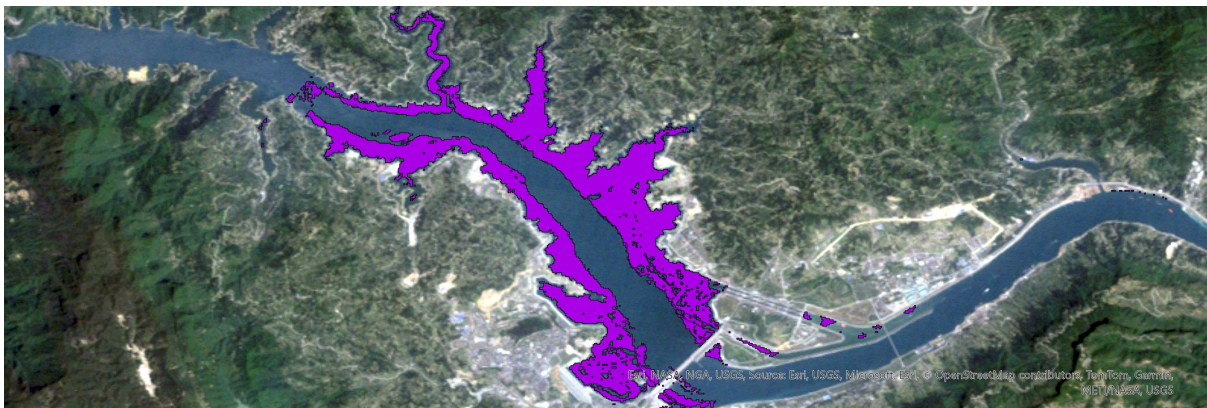
Figure IA I 4: These figures illustrate the identification of a wind plant footprint using Sentinel-2 satellite data. The plant is the Roaring Brook Wind Farm in New York State, U.S., with a capacity of 79.7 MW. The top picture shows the original satellite image. The bottom picture illustrates the plant detection algorithm, with the wind turbines colored in purple.



(a) original image - before dam construction



(b) original image - after dam construction



(c) plant detection algorithm

Figure IA I 5: These figures illustrate the identification of a hydro plant footprint using Sentinel-2 satellite data. The plant is the Three Gorges Dam in China with a capacity of 22,820 MW. The top picture shows the original satellite image before the dam was constructed. The middle picture shows the the original satellite image after the dam was constructed. The bottom picture illustrates the plant detection algorithm, with the area affected by the hydro plant colored in purple.



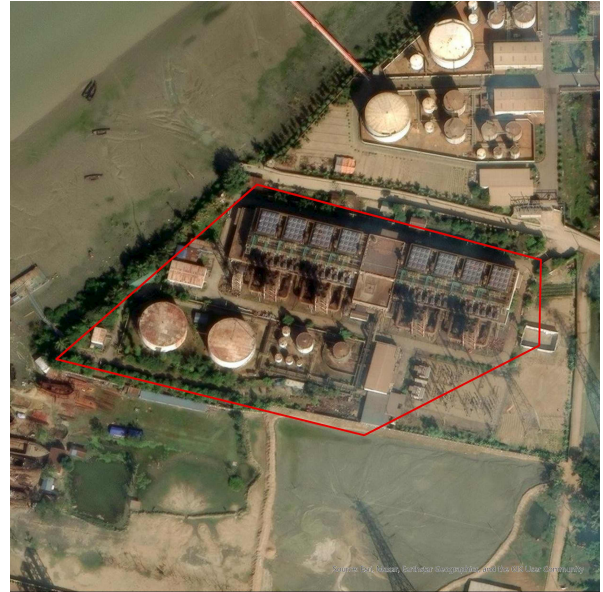
(a) Dalate Steam Plant (Coal) in Dalate, China



(b) Ostrovets Nuclear Power Plant in Astravyets, Belarus



(c) Ceredo Power Plant (Gas) in Ceredo, USA



(d) Energypac Internal Combustion Plant (Oil) in Patiya, Bangladesh

Figure IA I 6: This figure illustrates the manually delineated land-use boundaries of fossil-fuel based power plants. The examples are a 4,180 MW coal plant in China, a 2,388 MW nuclear plant in Belarus, a 519 MW gas Plant in USA, and a 108 MW gas plant in Bangladesh.

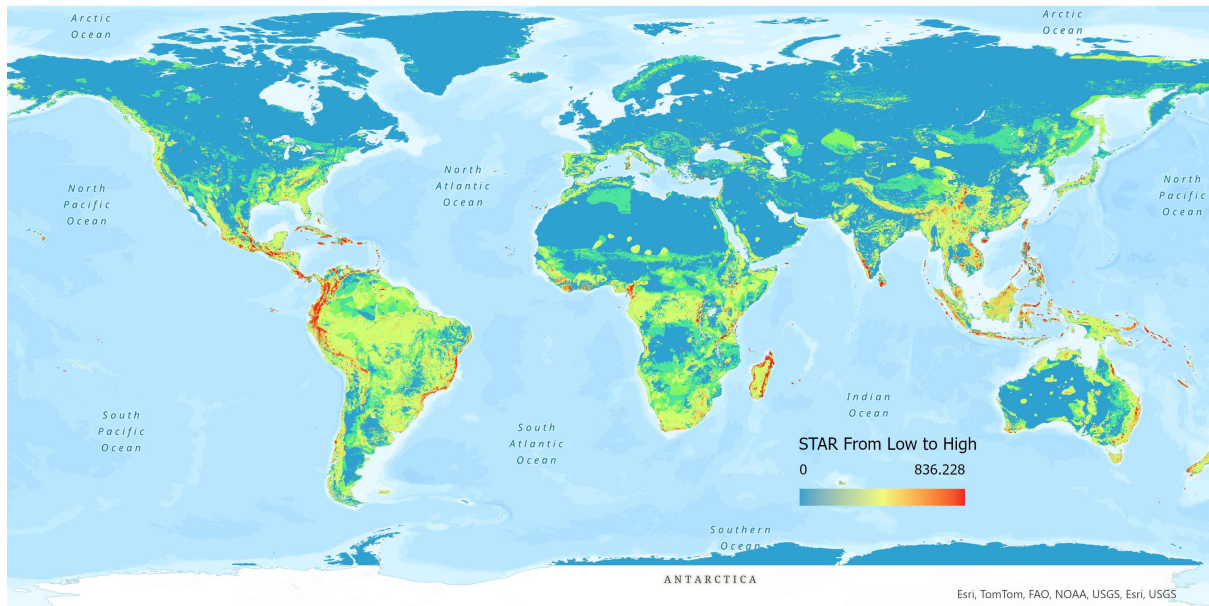


Figure IA I 7: This figure illustrates the Species Threat Abatement ($STAR_T$) scores that we use to calculate the biodiversity impact of RE power plants. The $STAR_T$ score reflects the potential for conservation efforts in a specific area. The color indicates the $STAR_T$ score, with blue representing low scores and red high scores.

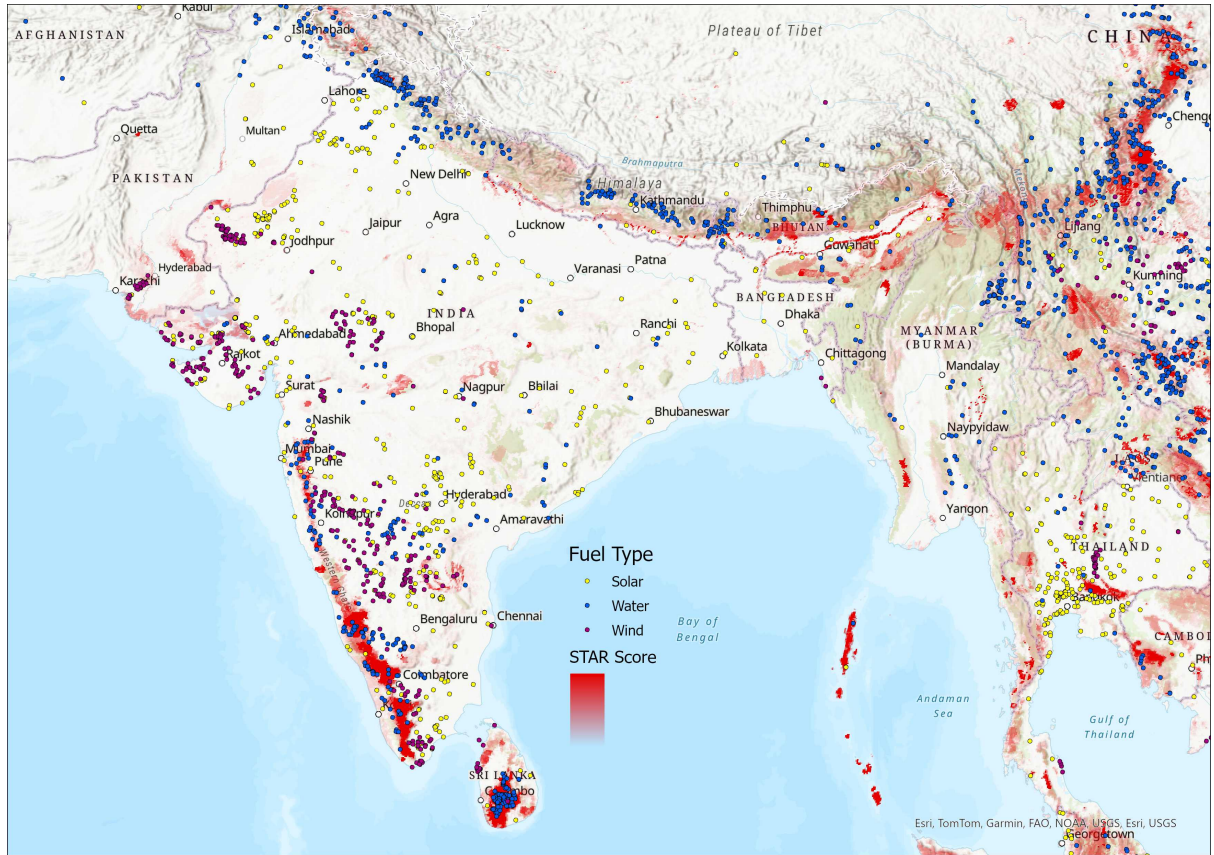


Figure IA I 8: This figure illustrates the spatial relationship between RE power plants and STAR_T scores in South Asia. Solar plants are in yellow, wind plants in purple, and hydro plants in blue. Areas with high STAR_T scores are colored in red.

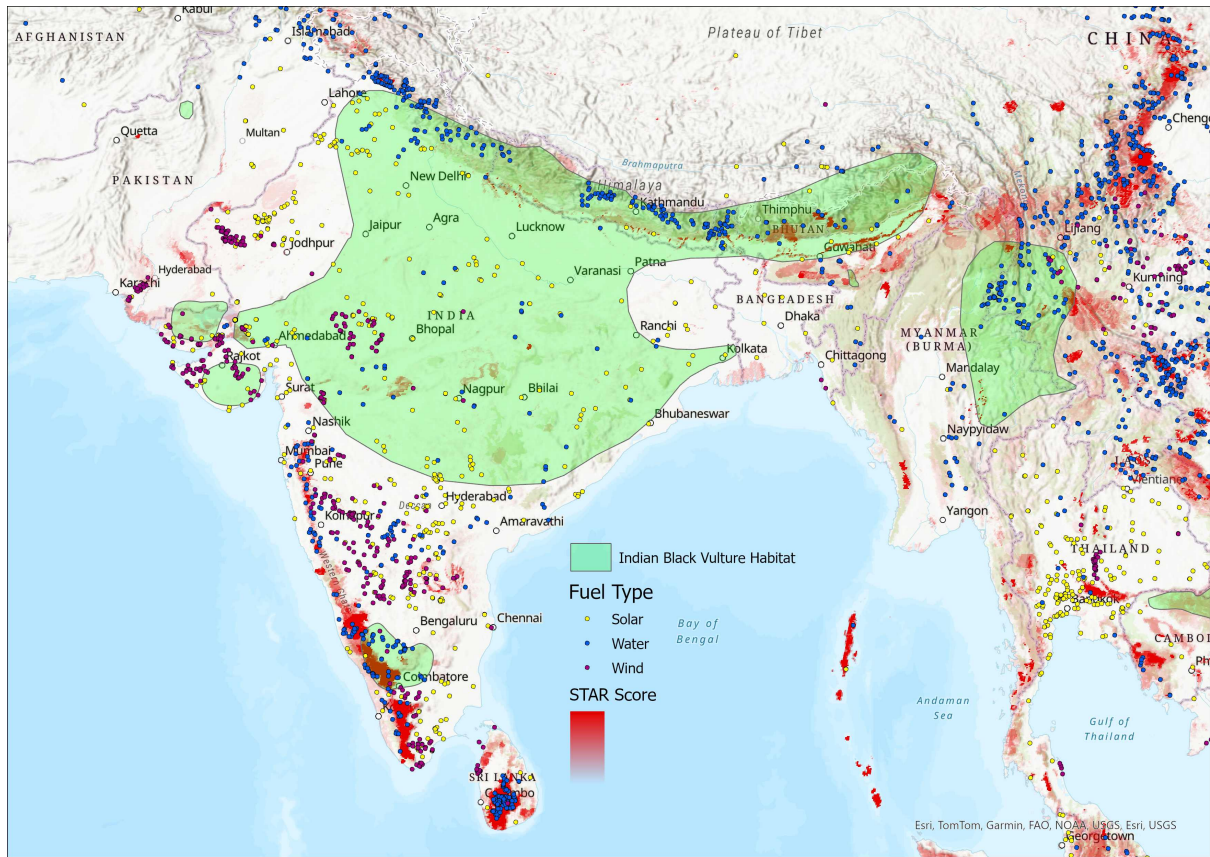


Figure IA I 9: This figure illustrates the area of habitat for the Indian Black Vulture (*Sarcogyps calvus*) as well as the locations of RE power plants in South Asia.



Figure IA I 10: These figures illustrate the location of the Romainville Solar Plant on the Seychelles. The picture on the left is a satellite image of the plant and the pictures on the right are maps on which the Seychelles are highlighted with a yellow dot.

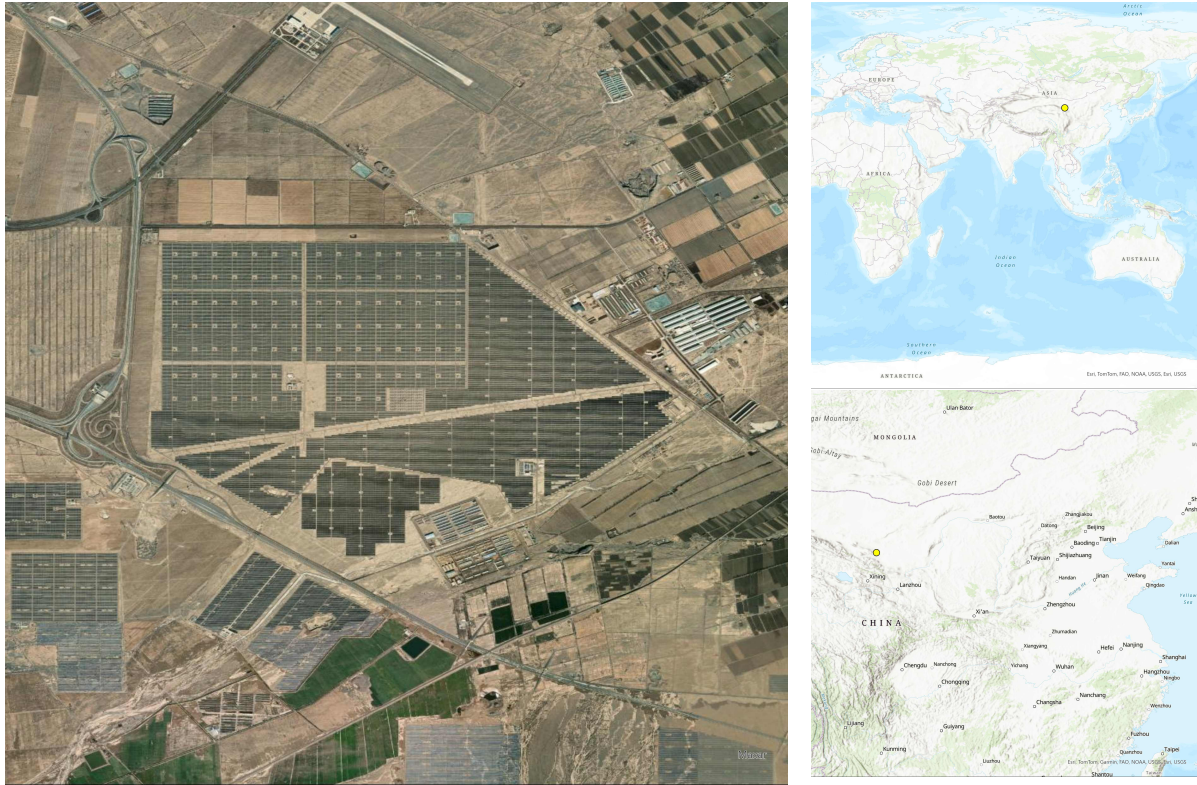


Figure IA I 11: This figure illustrates the location of the Jinchang Jinchuan Solar Plant in the Gobi Desert. The picture on the left is a satellite image of the plant and the pictures on the right side are maps on which the location is highlighted with a yellow dot.

Table IA I 1: STAR_T and Number of Species

	Log STAR _T				
	(1)	(2)	(3)	(4)	(5)
#Species (all)	0.0082*** (40.8)				
#Species (NT)		0.12*** (29.7)			
#Species (VU)			0.22*** (45.7)		
#Species (EN)				0.43*** (53.0)	
#Species (CR)					0.37*** (22.0)
Observations	40,674	40,674	40,674	40,674	40,674
Adj. R ²	0.10	0.058	0.11	0.14	0.029

The dependent variable is the natural logarithm of the STAR_T score of a power plant unit. #Species stands for number of species, NT for “Near Threatened”, VU for “Vulnerable”, EN for “Endangered”, and CR for “Critically Endangered.” *t*-statistics based on robust standard errors clustered by power plants are presented in parentheses. ***, ** and * indicate significance at the 1%-, 5%- and 10%-levels, respectively. Variables definitions can be found in [Appendix A](#).

Table IA I 2: $STAR_T$ Scores in Selected Countries

Country	Overall		Forested area		Grass land		Bare land	
	$STAR_T$ (in billion)	$STAR_T$ (per m^2)	$STAR_T$ (in billion)	$STAR_T$ (per m^2)	$STAR_T$ (in billion)	$STAR_T$ (per m^2)	$STAR_T$ (in billion)	$STAR_T$ (per m^2)
Indonesia	2,000.99	1.06	1,825.57	1.16	66.85	0.42	3.40	2.52
Mexico	1,804.42	0.93	1,396.04	2.17	267.41	0.31	20.10	0.07
Brazil	1,484.21	0.17	889.63	0.18	485.06	0.16	0.51	0.16
China	998.02	0.11	679.63	0.31	168.93	0.08	71.84	0.02
India	948.32	0.32	719.83	1.26	107.32	0.12	19.57	0.13
Australia	892.74	0.12	499.22	0.55	281.88	0.06	48.61	0.03
United States	766.02	0.08	388.86	0.15	209.38	0.06	46.00	0.05
Vietnam	355.17	1.08	330.12	1.62	14.39	0.35	0.03	0.06
Japan	266.67	0.71	210.34	0.86	5.65	0.39	0.76	5.06
Chile	209.46	0.28	103.53	0.56	43.59	0.25	45.50	0.15
Thailand	119.95	0.23	102.10	0.42	5.28	0.09	0.00	0.14
Spain	93.72	0.19	41.72	0.33	31.06	0.15	8.89	0.86
Turkey	80.49	0.10	29.33	0.22	33.69	0.09	5.77	0.17
Italy	68.68	0.23	38.55	0.43	18.00	0.24	0.06	0.08
Canada	55.67	0.01	29.70	0.01	17.51	0.00	1.31	0.00
Nepal	47.05	0.32	25.49	0.38	11.89	0.32	3.23	0.22
Greece	21.50	0.16	6.84	0.15	10.54	0.23	0.03	0.42
Romania	18.86	0.08	2.62	0.03	10.07	0.14	0.00	0.09
France	17.46	0.03	9.39	0.06	4.23	0.03	0.05	0.07
Portugal	9.64	0.11	3.65	0.13	3.05	0.08	0.01	0.12
Austria	7.80	0.09	5.57	0.15	1.11	0.07	0.00	0.01
Germany	4.08	0.01	2.72	0.03	0.48	0.01	0.00	0.00
Norway	3.97	0.01	0.72	0.01	2.72	0.02	0.17	0.01
Poland	3.57	0.01	2.40	0.02	0.68	0.01	0.00	0.01
Sweden	2.64	0.01	0.97	0.00	1.30	0.01	0.08	0.02
Switzerland	0.43	0.01	0.20	0.02	0.11	0.01	0.00	0.00
United Kingdom	0.38	0.00	0.05	0.00	0.27	0.00	0.00	0.00
Ireland	0.10	0.00	0.01	0.00	0.08	0.00	0.00	0.00
Belgium	0.06	0.00	0.02	0.00	0.01	0.00	0.00	0.00
Netherlands	0.06	0.00	0.01	0.00	0.02	0.00	0.00	0.00

This table presents $STAR_T$ scores (in billions and per m^2) for the 30 countries with the most RE plants in our sample, both for the overall country and separately for different land types.

Table IA I 3: Quantification of Biodiversity Impacts by Continent

Variable	Obs.	Mean	p25	p50	p75	SD
Panel A: RE Plants in Africa						
STAR _T [tsd]	761	366.04	0.72	5.14	44.53	5,478.73
STAR _T /kW	761	109.56	0.02	0.30	2.35	1,245.95
STAR _T /1,000m ²	761	900.30	6.33	26.84	126.00	8,123.63
Area [km ²]	761	1.06	0.03	0.33	0.67	2.93
Capacity [MW]	761	47.18	4.40	16.40	65.00	66.89
Panel B: RE Plants in Americas						
STAR _T [tsd]	11,379	205.98	1.23	7.26	30.02	3,678.73
STAR _T /kW	11,379	23.05	0.09	0.90	4.02	395.43
STAR _T /1,000m ²	11,379	550.78	5.37	18.60	81.37	3,186.40
Area [km ²]	11,379	0.87	0.13	0.46	0.64	2.20
Capacity [MW]	11,379	37.65	2.10	7.30	35.00	73.04
Panel C: RE Plants in Asia/Oceania						
STAR _T [tsd]	13,302	184.22	0.54	4.42	31.85	1,348.98
STAR _T /kW	13,302	27.53	0.04	0.25	1.83	308.35
STAR _T /1,000m ²	13,302	957.10	7.76	48.67	256.63	5,524.89
Area [km ²]	13,302	0.56	0.02	0.13	0.44	2.06
Capacity [MW]	13,302	50.14	4.20	15.00	49.50	107.62
Panel D: RE Plants in Europe						
STAR _T [tsd]	15,469	15.62	0.03	0.16	1.16	394.25
STAR _T /kW	15,469	2.95	0.01	0.02	0.16	85.96
STAR _T /1,000m ²	15,469	40.97	0.91	2.88	11.03	402.19
Area [km ²]	15,469	0.21	0.02	0.06	0.27	0.84
Capacity [MW]	15,469	15.26	3.00	7.20	16.00	29.45

This table quantifies the biodiversity impact and presents descriptive statistics for other related variable by continent. Variable definitions can be found in [Appendix A](#).

Table IA I 4: Ownership Overview

Category	Direct		Ultimate	
	Obs.	%	Obs.	%
Banks	435	0.7%	738	1.2%
Endowment	134	0.2%	393	0.6%
Government-related	2,116	3.3%	2,889	4.5%
Government	1,464	2.3%	1,601	2.5%
Hedge Fund	30	0.0%	39	0.1%
Industry	4,270	6.6%	6,728	10.5%
Insurance	509	0.8%	654	1.0%
Investor-Owned Utility	14,734	22.9%	14,274	22.3%
Mutual Fund	242	0.4%	131	0.2%
N/A	934	1.5%	883	1.4%
Other	405	0.6%	647	1.0%
Private Equity	3,900	6.1%	5,105	8.0%
Pension	323	0.5%	363	0.6%
Public Utility	32,734	50.9%	27,913	43.6%
RE Developer	2,109	3.3%	1,726	2.7%
Sum	64,339	100.0%	64,084	100.0%

This table presents an overview on the classifications of the direct and ultimate owners of RE power plant units.

Internet Appendix II: Comparison of the STAR Metric with Other Biodiversity Metrics

A. Overview and Goal

In this Internet Appendix, we compare the STAR metric with several other biodiversity metrics. We use two case studies to illustrate the different measurements and their limitations in our setting. The two case studies, a solar plant located in a desert region in Section B and a solar plant in a tropic region in Section C, are selected to highlight the measurements in two very different biodiversity settings. We also present a summary of the different alternative metrics and their limitations in Table IA II 1.

To ensure a comprehensive evaluation, our selection of metrics aligns with three direct biodiversity measurement categories from the EU Business & Biodiversity Platform (Lammerant et al., 2022). We contrast species-based metrics (STAR, Species Richness) against widely used extent $\times$ condition metrics (MSA and Species Loss Characterization Factors) and extent $\times$ condition $\times$ significance metrics (BII and Marginal Value of Persistence), thereby covering the primary types of measurement approaches available for plants-level estimation.

B. Case Study: Solar PV Plant in China

1. Description of Case Study

This case presents and calculates different biodiversity metrics for the Guazhou Solar Power Plant (100 MW) in Guazhou, China, a desert region in Gansu Province. The satellite imagery below show the plant and surrounding landscape. The plant started in 2015.



2. Biodiversity Scores

2.1. STAR Metric

Score: Combining the satellite-derived footprint of 2.48 km² with the local STAR_T index values yields a STAR_T score of 5,953 (calculated for the year 2015 in which the plant started).

Assessment: The score accounts for species in this desert ecosystem that are threatened by the project. Notably, despite the significantly larger land footprint of the Guazhou solar farm compared to the Flandes plant in Section C (2.48 km² vs. 0.54 km²), this plant’s biodiversity impact is about 12 times lower (5,953 vs. 71,752). Hence, the STAR metric captures the dramatic difference in local biodiversity richness and extinction risk between a species-poor desert biome and a tropical biodiversity hotspot.

2.2. Biodiversity Intactness Index (BII)

Methodology Estimates the average abundance of native species in an area relative to an undisturbed baseline. It combines models of total species abundance with measures of compositional similarity to a pristine reference ecosystem. The resulting intactness metric uses modeled relationships derived from the PREDICTS database, incorporating pressures such as land-use intensity, human population density, and road proximity. A key source for the method is [De Palma et al. \(2021\)](#).

Score: Percentage on a continuous scale from 0% (completely depleted) to 100% (pristine conditions). Since BII data are publicly available only at the country level, the regional average score for China is used. In the case of the plant, the BII score is ~63% for the year 2015 (BII scores are yearly observation).

Assessment: The average score cannot be linked to specific plants because it is aggregated at regional levels (e.g., country or ecoregion), lacking the spatial precision needed for project-specific impact evaluation. Crucially, intactness in a desert biome is not comparable to intactness in a tropical biodiversity hotspot. This is a primary limitation because it quantifies ecosystem degradation relative to a baseline rather than absolute species richness, making cross-biome comparisons problematic (a species-poor desert can score 100% if undisturbed, while a degraded but species-rich tropical forest might score lower). Furthermore, as a pre-packaged model dependent on simulated time-panels rather than dynamic ground-based observations, BII does not offer the flexibility to combine biodiversity indices with specific land-use data. Finally, BII scores lack additivity and cannot be meaningfully aggregated across projects.

2.3. Mean Species Abundance (MSA)

Methodology: Expresses the mean abundance of original species in a disturbed area as a proportion of their abundance in an undisturbed reference habitat. The calculation

incorporates six pressures: land-use change, infrastructure development, habitat fragmentation, human encroachment, nitrogen deposition, and climate change. The framework covers six major taxonomic groups, including mammals, birds, and plants. The metric is model-based, relying on established pressure-impact relationships from the GLOBIO framework. A technical guide for the method is [Dionisio et al. \(2023\)](#).

Score: Percentage on a scale from 0% (completely destroyed) to 100% (fully intact). In the case of the plant, the regional average derived from global pressure models (GLOBIO) is about $\sim 82.6\%$ in 2015.

Assessment: The method provides a more detailed, district-level assessment compared to BII, assigning a high score ($\sim 82.6\%$) to the Guazhou plant to indicate that the desert is relatively “untouched.” However, this is potentially misleading because a high percentage of intactness in a species-poor area does not equate to high biodiversity value. This reflects the metrics’ fundamental limitation: it indicates “how much is left” but does not quantify absolute species richness or extinction risk (“what is there”). Hence, the metric suffers from spatial incomparability, as high scores simply indicate an area is undisturbed regardless of its underlying ecological value. The metric fails to reflect the real impact of local infrastructure projects because it is model-based, relying on established pressure-impact relationships rather than direct species impacts.

2.4. *Species Richness*

Methodology: Estimates biodiversity by counting the number of species present within a standardized grid cell, including counts of threatened species and species with small geographic ranges. The calculation involves overlaying species range maps onto a global 10×10 km grid. Data inputs include breeding ranges for birds and IUCN Red List range maps for mammals and amphibians. A key source for the method is ([Jenkins et al., 2013](#)).

Score: Count of the number of species present within an area. In the case of the plant, approximately ~ 133 species, estimated by calculating the spatial intersection between the Guazhou plant’s land-use footprint and IUCN Red List area-of-habitat maps for mammals, amphibians, and birds.

Assessment: The low count accurately reflects the relatively low biodiversity richness of the desert biome. However, the metric treats all species equally; for example, a common lizard counts the same as a critically endangered bird. This fails to distinguish material extinction risk or to capture the relative urgency of conservation action. Additionally, the method acts as a coarse filter, using broad range maps rather than Area of Habitat maps, which means species may be counted as present even if their actual habitat within a grid cell has been destroyed. Finally, the metric provides no insight into the specific ratio/area of habitat impacted by renewable energy plants.

2.5. Species Loss Characterization Factors

Methodology: Uses a Countryside Species-Area Relationship (c-SAR) model to predict the number of global species extinctions attributable to different land-use types. The method derives a single Characterization Factor (CF) for each land-use category across 804 terrestrial ecoregions worldwide (rather than at the grid cell level). CFs are weighted using a Vulnerability Score (VS) calculated as the ratio of threatened endemic species richness to total species richness within each ecoregion. A key source for the method is [Chaudhary et al. \(2015\)](#).

Score: Fractional loss of species relative to a baseline, scaled by area and time. In the case of the plant, the score ranges between 1.5×10^{-15} and 6.4×10^{-16} , calculated as the ratio of the global species pool lost per m^2 , depending on the land-use type and based on the ecoregion average for the Taklimakan Desert (the closest ecoregion to Guazhou).

Assessment: This approach applies a generic coefficient to an entire ecoregion, assuming that the biodiversity value of the project location is identical to the rest of the Taklimakan Desert. This introduces significant measurement error. Guazhou is situated in an oasis ecosystem at the edge of the Gobi Desert, featuring a desert-oasis ecotone with distinct vegetation communities, agricultural lands, and water resources. In contrast, the Taklimakan is a hyper-arid shifting-sand desert where approximately 85% of the land consists of mobile, unstabilized dunes devoid of vegetation. This highlights the metric's primary limitation of coarse spatial resolution, where biodiversity impacts are averaged across entire ecoregions, ignoring site-level variation in habitat quality. Furthermore, the methodology was developed for Life Cycle Assessment (LCA) product-footprinting objectives rather than site-specific conservation targeting, making it less suited for evaluating individual infrastructure projects at precise locations.

2.6. Marginal Value of Persistence

Methodology: Quantifies how land conversion affects the probability of local species persistence. It employs a non-linear power law relationship ($P = E^z$) to estimate a persistence score based on remaining habitat area, then distributes the marginal change in persistence (ΔP) across converted land cells. Required inputs include high-resolution Area of Habitat (AOH) maps and historical baseline vegetation data representing pre-anthropogenic conditions. A key source for the method is [Durán et al. \(2020\)](#).

Score: Persistence score (P) between 0 and 1 calculated as $P = E^z$ with E being the proportion of original habitat remaining and z the extinction coefficient (typically 0.25). In the case of the plant, data are not available to evaluate the plant.

Assessment: The metric requires accurate historical baseline maps (e.g., pre-16th-century vegetation) to calculate habitat depletion curves. Such data are not available for many region, rendering the methodology often inapplicable. Beyond this high data

requirement, the metric is designed for attribution rather than opportunity identification, focusing on ex-post assignment of responsibility for historical biodiversity loss rather than ex-ante identification of conservation intervention opportunities. Lastly, there is an aggregation problem: the non-linear nature of the persistence function makes simple addition of marginal values across a portfolio of sites mathematically complex and potentially inconsistent for applications that require additive metrics.

C. Case Study: Solar PV Plant in Colombia

1. Description of Case Study

This case presents biodiversity metrics for the Flandes Planta de Energía Solar (28.1 MW) located in Flandes, Colombia, a tropical region in the Magdalena Valley of the Andes. The satellite imagery below shows plant and surrounding landscape. The plant started in 2023.



2. Biodiversity Scores

2.1. STAR Metric

Score: Combining the satellite-derived footprint of 0.54 km² with local STAR_T index values yields a STAR_T score of 71,752 (start of the plant in 2023).

Assessment: Although the land footprint is about 4.6 times smaller than that of the Guazhou project, the total biodiversity impact is over 12 times higher. This demonstrates the metrics' sensitivity to local ecological conditions, accurately reflecting the high biodiversity density and extinction risk inherent to the tropical Andes.

2.2. Biodiversity Intactness Index (BII)

Score: Percentage on a continuous scale from 0% (completely depleted) to 100% (pristine conditions). In the case of the plant, using the country-level aggregate for Colombia, the regional average score is $\sim 72\%$ in 2023.

Assessment: The metric fails to reflect the massive difference in absolute biological richness between Guazhou and Flandes. While it suggests declining intactness over time, it misses the critical point that destroying one hectare here is far more damaging to global biodiversity than one hectare in a desert biome. This highlights a primary limitation: the metric measures ecosystem degradation relative to a baseline rather than absolute species richness; consequently, a species-poor desert can score 100% if undisturbed, while a degraded but species-rich tropical forest might score lower, making cross-biome comparisons problematic. Additionally, the “time-panel” is simulated based on changes in pressure inputs rather than dynamic ground-based observations, and the data is typically aggregated at regional levels (e.g., country or ecoregion), lacking the spatial precision needed for project-specific biodiversity-impact evaluation. Finally, as a pre-packaged model, it does not offer the flexibility to combine biodiversity indices with specific land-use data, and as with the Guazhou case, the metric lacks additivity and cannot be meaningfully aggregated across projects.

2.3. Mean Species Abundance (MSA)

Score: Percentage on a scale from 0% (completely destroyed) to 100% (fully intact). In the case of the plant, the regional average derived from GLOBIO models is approximately $\sim 21.6\%$ in 2023.

Assessment: MSA assigns a low score ($\sim 21.6\%$), correctly indicating habitat degradation, but paradoxically makes Flandes appear “less valuable” than Guazhou (21.6% vs. 82.6%). In reality, the per-area STAR density in Flandes is about 40 times higher than in Guazhou. This highlights a primary limitation: MSA is a relative intactness measure indicating the proportion of original biodiversity remaining (“how much is left”) rather than quantifying absolute species richness or extinction risk (“what is there”). Consequently, it suffers from spatial incomparability, where scores reflect disturbance levels rather than ecological value—for example, an intact desert and an intact tropical rainforest would both score highly despite vastly different species richness. Furthermore, the metric is model-based, relying on established pressure-impact relationships from the GLOBIO framework rather than direct species surveys. As a result, MSA fails to capture material biodiversity risk differences and cannot be meaningfully aggregated across assets.

2.4. Species Richness

Score: Count of the number of species present within an area. In the case of the plant, about ~ 445 species, estimated through spatial intersection with IUCN Red List habitat maps.

Assessment: The high count accurately reflects the tropical diversity of the Magdalena Valley, but the metric treats all species equally regardless of their conservation status. Without risk-weighting, it fails to quantify the urgency of conservation in this valley. This highlights the method’s primary limitations: it acts as a coarse filter, using broad range maps rather than Area of Habitat (AOH) maps, which means species may be counted as present in a grid cell even if their actual habitat within that cell has been destroyed. Furthermore, by treating all threatened species equally regardless of their extinction risk level, it fails to capture the relative urgency of conservation action. Finally, the metric provides no insight into the specific ratio/area of habitat impacted by renewable energy plants.

2.5. Species Loss Characterization Factors

Score: Fractional loss of species relative to a baseline, scaled by area and time. In the case of the plant, the score ranges from 6.23×10^{-14} to 3.4×10^{-13} , calculated as the ratio of the global species pool per m^2 , depending on the land-use type and based on the ecoregion average for the Magdalena Valley dry forests.

Assessment: The approach assumes homogeneous biodiversity impact across the valley and cannot provide precise asset-level estimates. It ignores local habitat heterogeneity and the specific footprint of the solar plant, which spans dry forest fragments, agricultural land, and riparian corridors along the Magdalena River.

Assessment: This approach assumes homogeneous biodiversity impact across the valley and cannot provide precise asset-level estimates. It ignores local habitat heterogeneity and the specific footprint of the solar plant, which spans dry forest fragments, agricultural land, and riparian corridors along the Magdalena River. This illustrates the metric’s primary limitation of coarse spatial resolution, where biodiversity impacts are averaged across entire ecoregions, assuming homogeneity within large geographic areas. Additionally, the methodology was developed for Life Cycle Assessment (LCA) applications, where the goal is to estimate the biodiversity footprint embedded in products (e.g., comparing bioethanol feedstocks). This product-footprinting objective differs fundamentally from site-specific conservation targeting, where the aim is to evaluate the biodiversity impact of individual infrastructure projects at precise locations.

2.6. Marginal Value of Persistence

Score: Persistence score (P) between 0 and 1 calculated as $P = E^z$ with E being the proportion of original habitat remaining and z the extinction coefficient (typically 0.25).

In the case, data are not available to assess the plant.

Assessment: The methodology relies on historical baseline vegetation maps to estimate habitat depletion curves. Such baselines are only available for select regions, rendering the metric unsuitable for global, asset-level biodiversity analysis. Beyond this high data requirement, the metric is designed for attribution rather than opportunity identification, focusing on ex-post assignment of responsibility for historical biodiversity loss rather than ex-ante identification of conservation intervention opportunities. Lastly, there is an aggregation problem: the non-linear nature of the persistence function makes simple addition of marginal values across a portfolio of sites mathematically complex and potentially inconsistent for applications that require additive metrics.

Table IA II 1: Alternative Biodiversity Metrics

Metric	Methodology	Score	Limitations	Applications
Biodiversity Intactness Index (BII)	Estimates the average abundance of native species in a given area relative to an undisturbed baseline. The metric uses modeled relationships derived from the PREDICTS database, incorporating pressures such as land use intensity, human population density, and road proximity.	Percentage on a continuous scale ranging from 0% (completely depleted) to 100% (pristine conditions).	- Measures ecosystem degradation relative to a baseline rather than absolute species richness; consequently, a species-poor desert can score 100% if undisturbed, while a degraded but species-rich tropical forest might score lower, making cross-biome comparisons problematic. - Is “time-panel” simulated based on changes in pressure inputs rather than dynamic ground-based observations. - Is typically aggregated at regional levels (e.g., country or ecoregion), lacking the spatial precision needed for project-specific biodiversity-impact evaluation. - metric is based on a pre-packaged model and does not offer the flexibility to combine biodiversity indices with specific land-use data.	Schneider et al. (2024) utilize the BII to model trade-offs in future land-use scenarios, projecting that a profit-driven global cropland expansion of 3.6% by 2030 would result in a 26% decline in biodiversity intactness within the newly expanded areas.
Mean Species Abundance (MSA)	Expresses the mean abundance of original species in a disturbed area as a proportion of their abundance in an undisturbed reference habitat. The calculation incorporates six pressures: land use change, infrastructure development, habitat fragmentation, human encroachment, nitrogen deposition, and climate change. The framework covers six major taxonomic groups, including mammals, birds, and plants. Builds on the GLOBIO model.	Percentage on a scale from 0% (completely destroyed) to 100% (fully intact).	- Is a relative intactness measure, which indicates the proportion of original biodiversity remaining (“how much is left”) rather than quantifying absolute species richness or extinction risk (“what is there”). - Suffers from spatial incomparability: high scores simply indicate that an area is relatively undisturbed but provide no information about the underlying ecological value. For example, an intact desert and an intact tropical rainforest would both score highly despite vastly different species richness. - Is model-based, relying on established pressure-impact relationships from the GLOBIO framework rather than direct species surveys.	Schipper et al. (2020) apply MSA to project global biodiversity trends under Shared Socioeconomic Pathways (SSPs), finding that land-use change remains the dominant driver of terrestrial biodiversity loss through 2050.
Species Richness	Estimates biodiversity by counting the number of species present within a standardized grid cell, including counts of threatened species and species with small geographic ranges. The calculation involves overlaying species range maps onto a global 10 × 10 km grid (using an equal-area projection). Data inputs include breeding ranges for birds and IUCN Red List range maps for mammals and amphibians.	Count of the number of species present within an area.	- Acts as a coarse filter, using broad range maps rather than Area of Habitat (AOH) maps that account for suitable habitat within a species’ range. This means species may be counted as present in a grid cell even if their actual habitat within that cell has been destroyed. - Has no risk weighting, treating all threatened species equally regardless of their extinction risk level and failing to capture the relative urgency of conservation action. - Faces an action gap: while species richness maps identify where species occur, they do not indicate what interventions would most effectively reduce extinction risk (e.g., threat abatement vs. habitat restoration).	Montesino Pouzols et al. (2014) integrate distribution data for 24,757 terrestrial vertebrate species into a spatial prioritization framework for global protected area expansion.

Continued on next page...

Table IA II 1 continued

Metric	Methodology	Score	Limitations	Applications)
Species Loss Characterization Factors	Uses a Countryside Species-Area Relationship (c-SAR) model to predict the number of global species extinctions attributable to different land use types. The method derives a single Characterization Factor (CF) for each land use category across 804 terrestrial ecoregions worldwide (rather than at the grid cell level). CFs are weighted using a Vulnerability Score (VS) calculated as the ratio of threatened endemic species richness to total species richness within each ecoregion.	Fractional loss of species relative to a baseline, scaled by area and time.	- Has a coarse spatial resolution: biodiversity impacts are averaged across entire ecoregions, assuming homogeneity within large geographic areas and ignoring site-level variation in habitat quality and species distributions. - Is designed to predict future species loss resulting from land use change, rather than to quantify current opportunities for reducing extinction risk. - Was developed for Life Cycle Assessment (LCA) applications, where the goal is to estimate the biodiversity footprint embedded in products (e.g., comparing bioethanol from different feedstocks). This product-footprinting objective differs fundamentally from site-specific conservation targeting, where the aim is to evaluate and compare the biodiversity impact of individual infrastructure projects at precise locations.	Chaudhary et al. (2015) apply characterization factors to compare land use biodiversity impacts of bioethanol production from six different feedstocks across world regions.
Marginal Value of Persistence	Quantifies how land conversion affects the probability of local species persistence. It employs a non-linear power law relationship ($P = E^z$) to estimate a persistence score based on remaining habitat area, then distributes the marginal change in persistence (ΔP) across converted land cells. Required inputs include high-resolution Area of Habitat (AOH) maps and historical baseline vegetation data representing pre-anthropogenic conditions.	Persistence score (P) between 0 and 1 calculated as $P = E^z$ with E being the proportion of original habitat remaining and z the extinction coefficient (typically 0.25).	- Has a high data requirement, requiring accurate historical baseline data (e.g., pre-16th century vegetation maps) that are often unavailable or unreliable at global scales. - Is designed for attribution rather than opportunity identification, focusing on ex-post assignment of responsibility for historical biodiversity loss rather than ex-ante identification of conservation intervention opportunities. - Brings an aggregation problem: the non-linear nature of the persistence function makes simple addition of marginal values across a portfolio of sites mathematically complex and potentially inconsistent for applications that require additive metrics.	Durán et al. (2020) apply the marginal value framework to the Brazilian Cerrado to assess biodiversity impacts of land conversion on over 2,000 species of amphibians, birds, mammals, and plants between 2000 and 2014.

This table compares various potential alternatives to the STAR metric. It explains the respective methodologies (definition, calculation, inputs) and provides assessments regarding each method’s limitations for site-specific measurements of biodiversity impacts. These assessments highlight why our approach employs the STAR metric. We also provide examples of research where the other metrics are used. The selection of metrics aligns with the biodiversity measurement categories by the EU Business & Biodiversity Platform ([Lammerant et al., 2022](#)).