Biodiversity Impacts of Renewable Energy

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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.

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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). Pursuing these 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 them 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.

Despite these developments, large scale, comprehensive evidence 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

[1]Asset 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).

[2]Biodiversity 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).

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 km^2 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 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

[3]Two 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.

[4]The 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).

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 sensitive 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 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

[5] A 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.

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.

Related Literature. 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 geo-

[6]Most 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.

graphic 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]

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

[7]Utility-scale RE capacity excludes small installations serving individuals or businesses, such as rooftop solar panels. Figure IA 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.

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 multispectral 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.

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

[8] Dynamic 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 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 3 for an illustration).

[10] By 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.

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 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 allocate 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 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 6 illustrates the delineated boundaries for four exemplary plants. Second, we

[11] Turbine 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 m^2, 22,050 m^2 for forest, 12,075 m^2 for grassland, and 14,400 m^2 for cropland (given an average capacity of 1.5 MW per turbine).

[12] As 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).

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%).

[13]Although 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.

[14]The 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.

E. Quantifying Biodiversity Impacts

We quantify the biodiversity impacts of RE plants due to land use using the STAR metric (Mair et al., 2021). Using a spatially explicit framework, this 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 (FfBF), 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 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 5×5 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 5×5 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]

[15] Data 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.

[16] Critically-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 5×5 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 ($0.01\times100 = 1$), and 5% of a least-concern species' habitat ($0.05\times0 = 0$),

Figure IA 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 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 1 shows its correlation with the number of species that are affected by a RE plant, a simpler yet less precise 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.

the STAR_T value for that pixel would be 3.0 ($= 2 + 1 + 0$).

[17] For 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).

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 25^{th} percentile value of 130, a median of 1,610, and a 75^{th} 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 m^2, 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 3, RE plants have the largest average biodiversity impacts in Africa (STAR_T score average of 366,040), followed by the Americas and Asia/Oceania. On a per-m^2 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

[18] Because 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.

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

[20] For comparison, Table IA 2 lists the aggregate STAR_T scores (total and per m^2) 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 m^2 occurs in Vietnam, Indonesia, and Mexico.[21] Because we apply our m^2-based STAR score to entire country in this table, the aggregate country-level numbers are large; a km^2 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 m^2 scale.

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 biodiversity impacts, for example the Jinchang Jinchuan Solar Plant (capacity of 200 MW), which is located in a the Gobi desert (see Figure IA 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

[22]The 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. 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 10 illustrates the location of the plant.

[23]Most affected is the House Mouse, for which 20,469 km^2 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

plants are also built within the habitats of critically-endangered species. An example is the California Condor, for which 1,161 km^2 (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 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 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 m^2 of land use in Panel (f). According to this metric, hydro plants are

its total habitat.

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

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 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.

[25] Power 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.

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 km^2 per plant in 2000 to approximately 0.7 km^2 in 2023. In terms of the $STAR_T$ score per 1,000 m^2, 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 m^2 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*, 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)

[26] Shive 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.

[27] While 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.

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.

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 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.

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

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

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 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

[30]Since 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).

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 fars 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]	Capacity of a power plant unit in MW. Source: S&P Market Intelligence.
Share $\text{RE}_{location}^{t-3}$	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.

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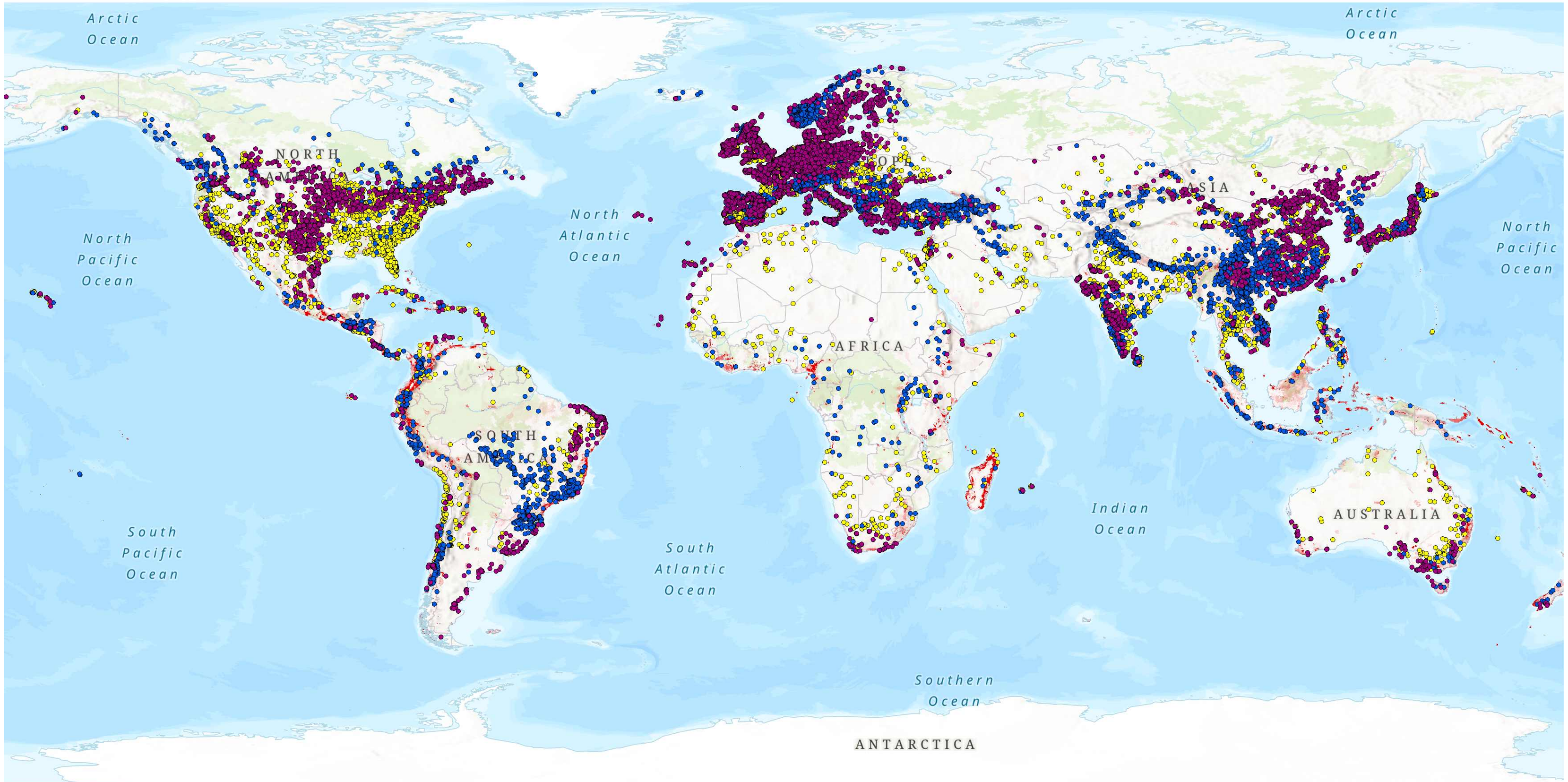
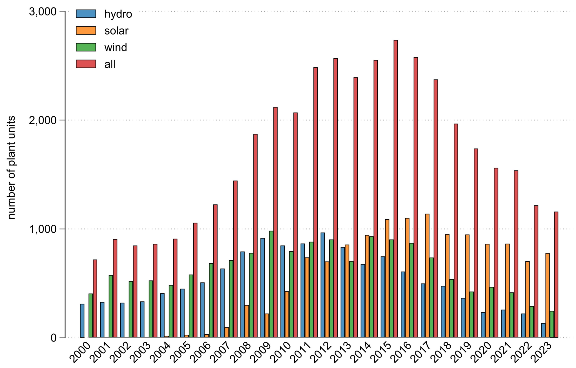
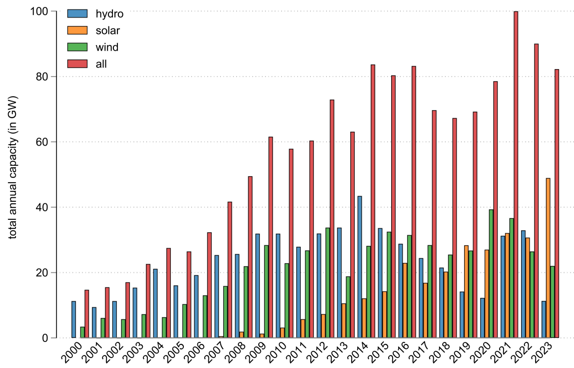


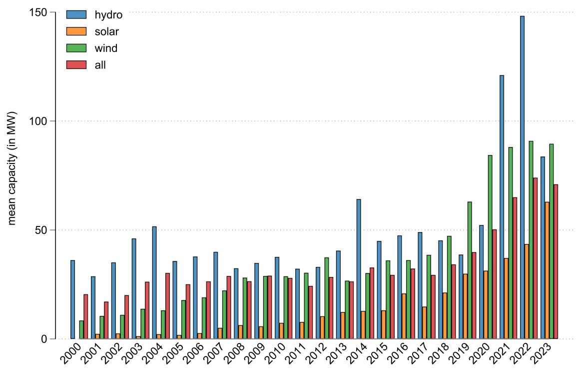
Figure 1: This figure shows the locations of solar plants (yellow), wind plants (purple), and hydro plants (blue) included in the sample. The plants became operational between 2000 and 2023 and meet the minimum capacity thresholds of 1 MW.



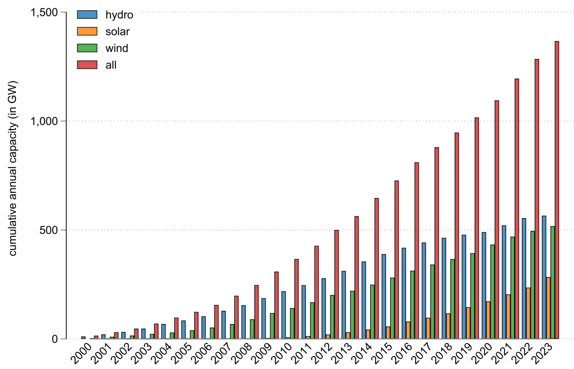
(a) Number of new plant units



(b) Total capacity of new plants

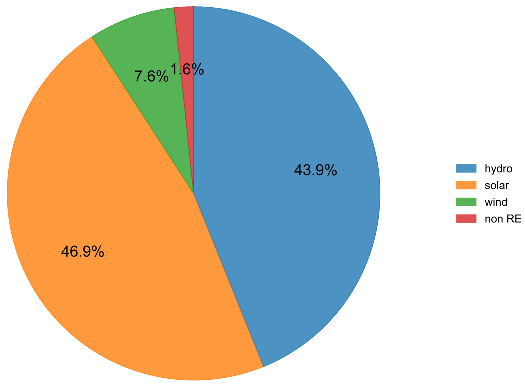


(c) Average capacity of new plants

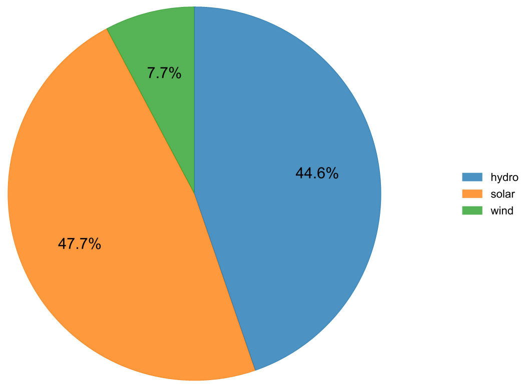


(d) Cumulative capacity

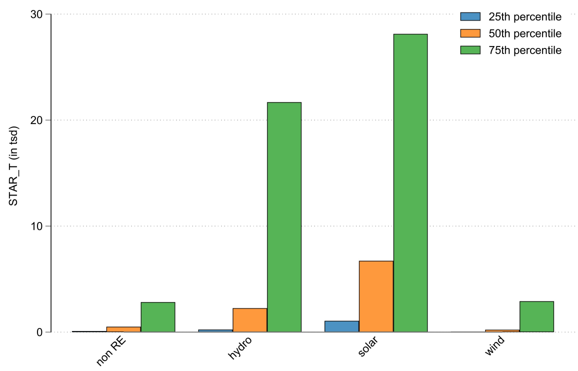
Figure 2: Panel (a) shows the number of new power plant units by technology and year. Panel (b) shows the total newly added capacity by year and technology and Panel (c) the average capacity of newly added plants by year and technology. Panel (d) shows the cumulative capacity by technology since 2000.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



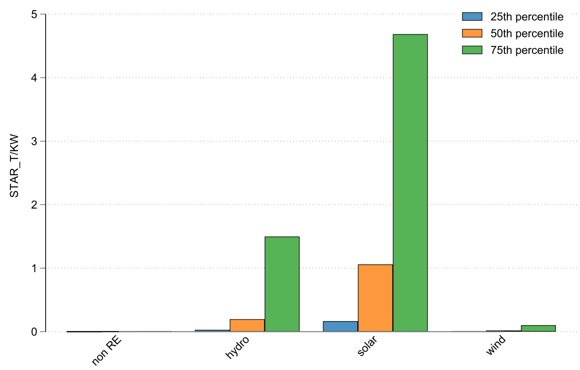
(a) Total STAR$_T$ score



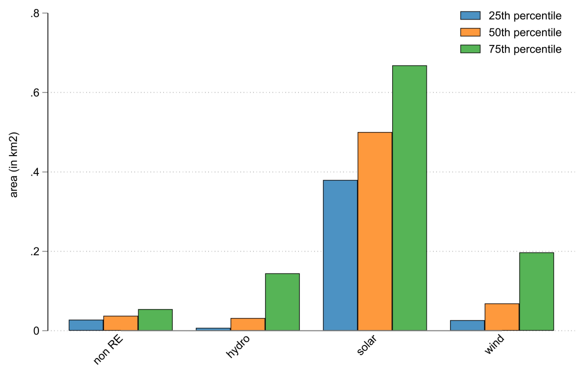
(b) Without non RE



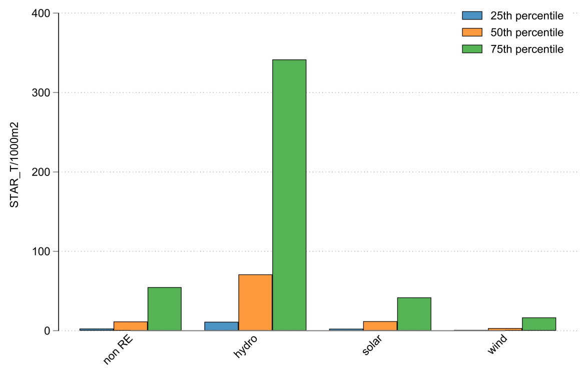
(c) STAR$_T$ per plant



(d) STAR$_T$ per kW

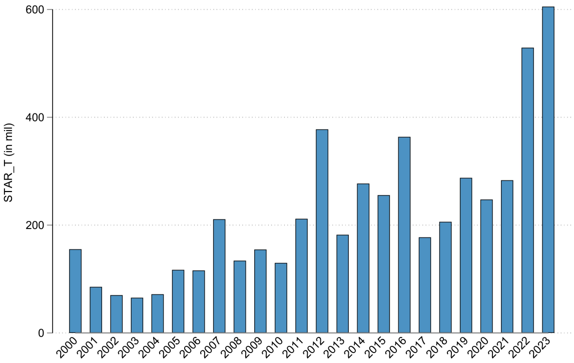


(e) Land use per plant in km^2

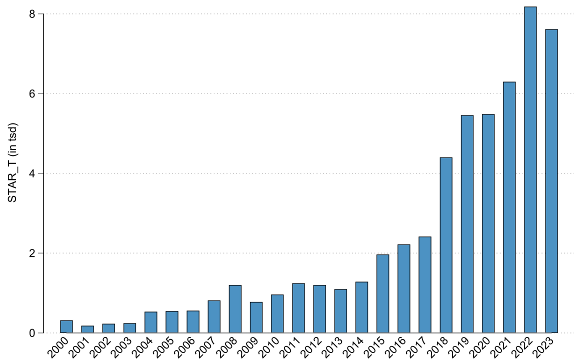


(f) STAR$_T$ per 1,000 m^2

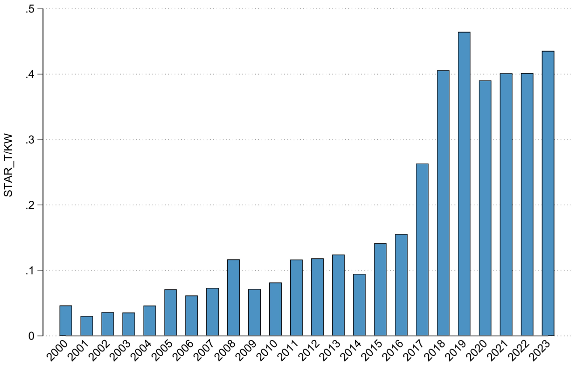
Figure 3: These figures show the land-use induced biodiversity impact of RE and non-RE plants by technology. Panels (a) and (b) show how much plant units with different technologies contribute to the total STAR$_T$ score (with and without non-RE plants). Panel (c) shows the 25th, 50th, and 75th percentile 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.



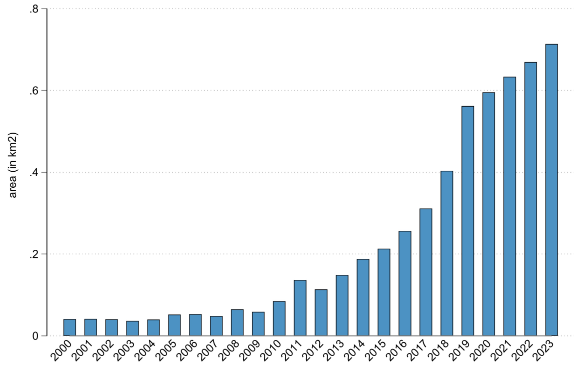
(a) Total STAR_T score



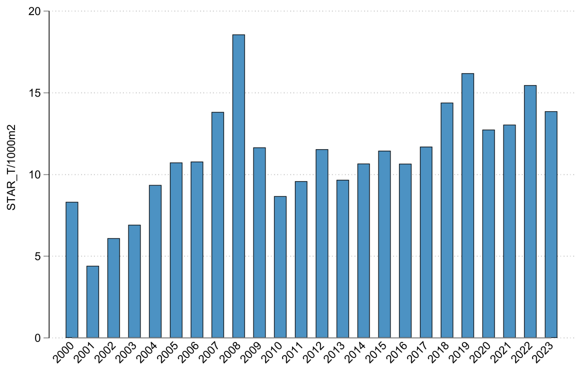
(b) STAR_T per plant



(c) STAR_T per kW

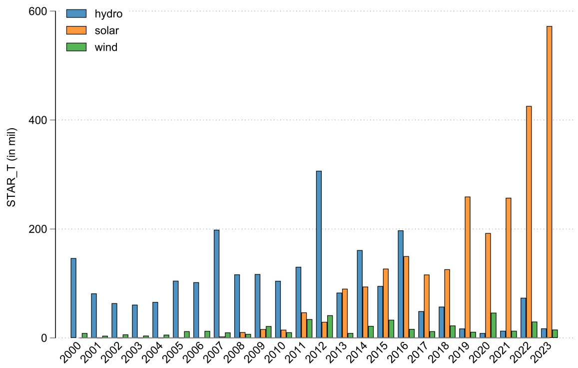


(d) Land use per plant in km^2

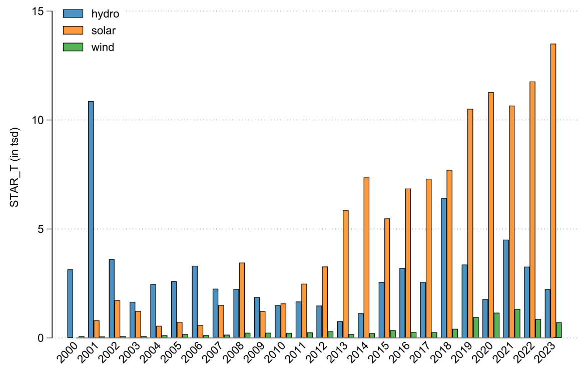


(e) STAR_T per 1,000 m^2

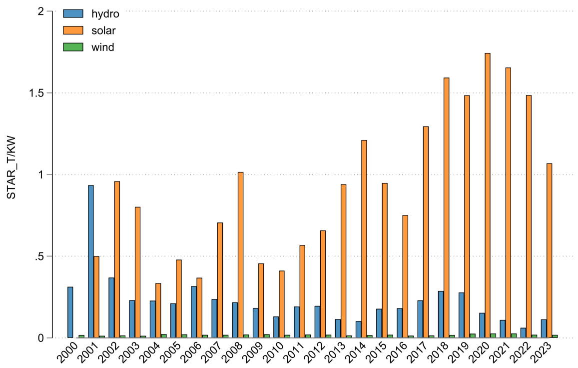
Figure 4: These figures show the land-use induced biodiversity impact of renewable power plants over time. Panel (a) shows the total STAR_T score. Panel (b) shows median STAR_T score in thousand per power plant unit. Panel (c) plots the median STAR_T score per kilowatt of capacity. Panel (d) shows the 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.



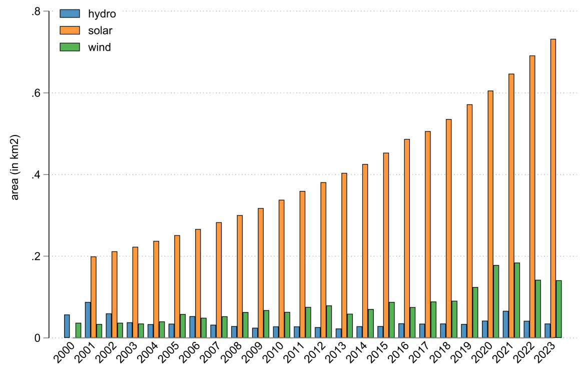
(a) Total STAR$_T$ score



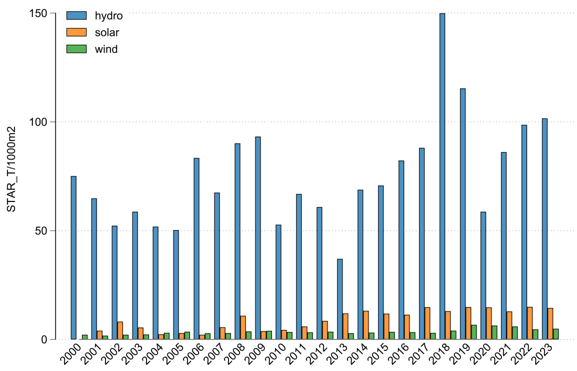
(b) STAR$_T$ per plant



(c) STAR$_T$ per kW



(d) Land use per plant in km^2



(e) STAR$_T$ per 1,000 m^2

Figure 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	$\text{STAR}_{\boldsymbol{T}}$ [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				
Mus musculus	Eastern House Mouse	LC	20,469	0.05%
Hirundo rustica	Barn Swallow	LC	19,915	0.70%
Pandion haliaetus	Fish Hawk	LC	18,513	0.10%
Ardea alba	American Egret	LC	18,233	0.14%
Falco peregrinus	Duck Hawk	LC	17,507	0.08%
Passer domesticus	House Sparrow	LC	15,925	0.07%
Tyto alba	Barn Owl	LC	15,180	0.05%
Bubulcus ibis	Cattle Egret	LC	14,920	4.38%
Asio flammeus	Short-eared Owl	LC	14,227	0.20%
Nycticorax nycticorax	Black-crowned Night Heron	LC	13,990	0.18%
Panel B: Critically-Endangered Species				
Aythya baeri	Baer's Pochard	CR	2,585	0.08%
Gyps bengalensis	Asian White-backed Vulture	CR	2,298	0.08%
Sarcogyps calvus	Indian Black Vulture	CR	1,880	0.08%
Vanellus gregarius	Sociable Lapwing	CR	1,223	0.08%
Emberiza aureola	Yellow-breasted Bunting	CR	1,217	0.06%
Gyps indicus	Indian Griffon	CR	1,213	0.10%
Gymnogyps californianus	California Condor	CR	1,161	0.98%
Mustela lutreola	European Mink	CR	1,141	0.13%
Campephilus principalis	Ivory-billed Woodpecker	CR	908	0.11%
Sypheotides indicus	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 bionmial 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 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***	2.80***	0.14**	0.14
	(43.6)	(38.2)	(1.99)	(1.47)
Wind	1.00***	1.09***	0.17***	0.17**
	(16.5)	(15.7)	(2.70)	(2.26)
Hydro	1.34***	1.40***	1.73***	1.73***
	(19.3)	(18.3)	(26.1)	(21.5)
Log Area [m^2]			0.99***	0.99***
			(94.0)	(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***	0.026***	0.0055**	0.0064**
	(7.43)	(7.24)	(2.15)	(2.42)
Log Area [m^2]			0.98***	0.99***
			(99.8)	(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***	2.11***	0.83**	0.81**
	(5.79)	(3.93)	(2.48)	(2.41)
Log Area [m^2]			0.99***	1.00***
			(101)	(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 $\text{RE}^{t-3}_{location}$, 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***	0.52***	0.067**	0.073**
	(6.05)	(6.13)	(2.31)	(2.50)
Log Area [m^2]			1.00***	1.02***
			(163)	(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***	-0.68***	-0.082**	-0.086**
	(-4.93)	(-5.02)	(-2.48)	(-2.56)
Log Area [m^2]			1.00***	1.02***
			(162)	(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

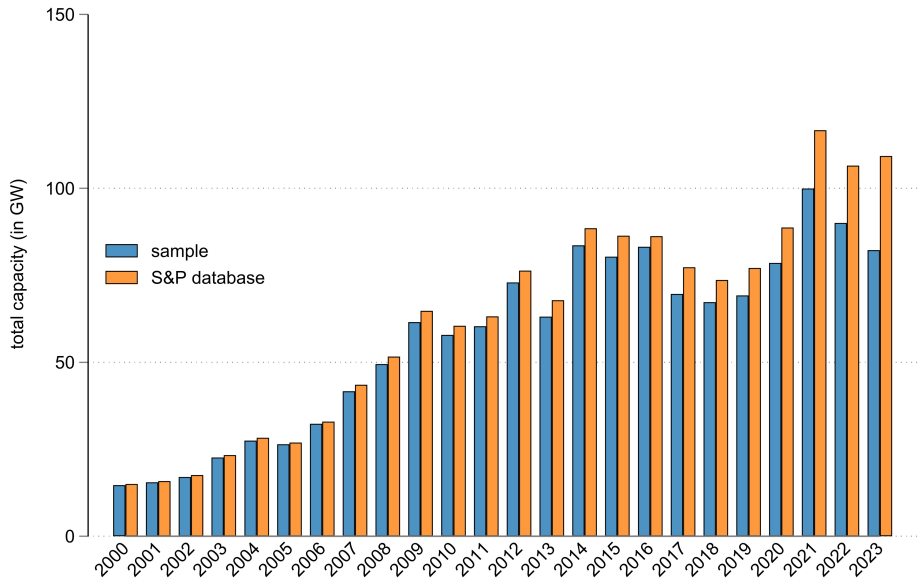
	Log $STAR_T$			
	(1)	(2)	(3)	(4)
Project Financed	-0.16**	-0.19***	-0.11***	-0.10***
	(-2.41)	(-2.90)	(-3.29)	(-3.24)
Log Area [m^2]			1.00***	1.01***
			(131)	(63.3)
Log Capacity [MW]				-0.0066
				(-0.37)
Observations	41,792	41,768	41,768	41,768
Adj. R^2	0.42	0.46	0.79	0.79
Technology × Year FE	Yes	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.

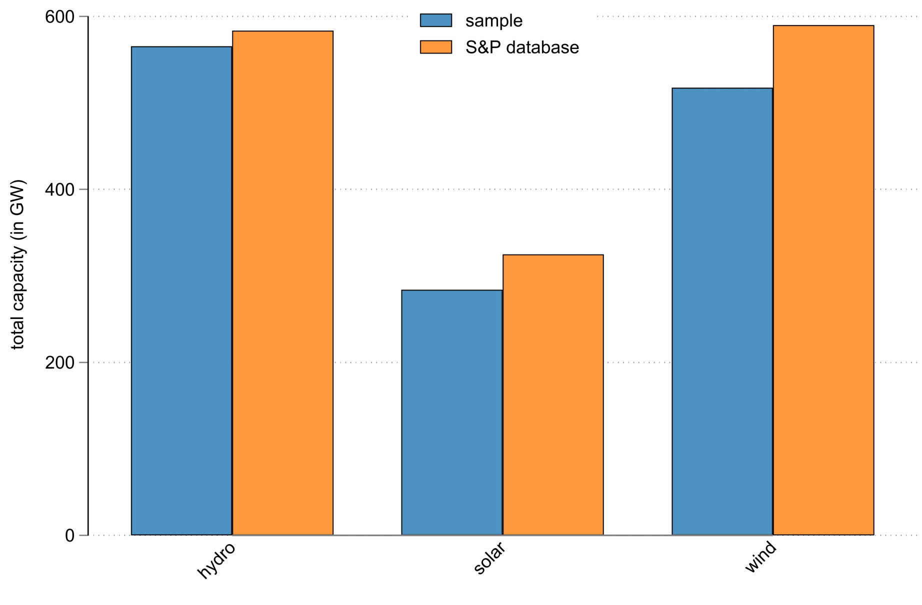
Internet Appendix

for

Biodiversity Impacts of Renewable Energy



(a) Comparison by year



(b) Comparison by technology

Figure IA 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).

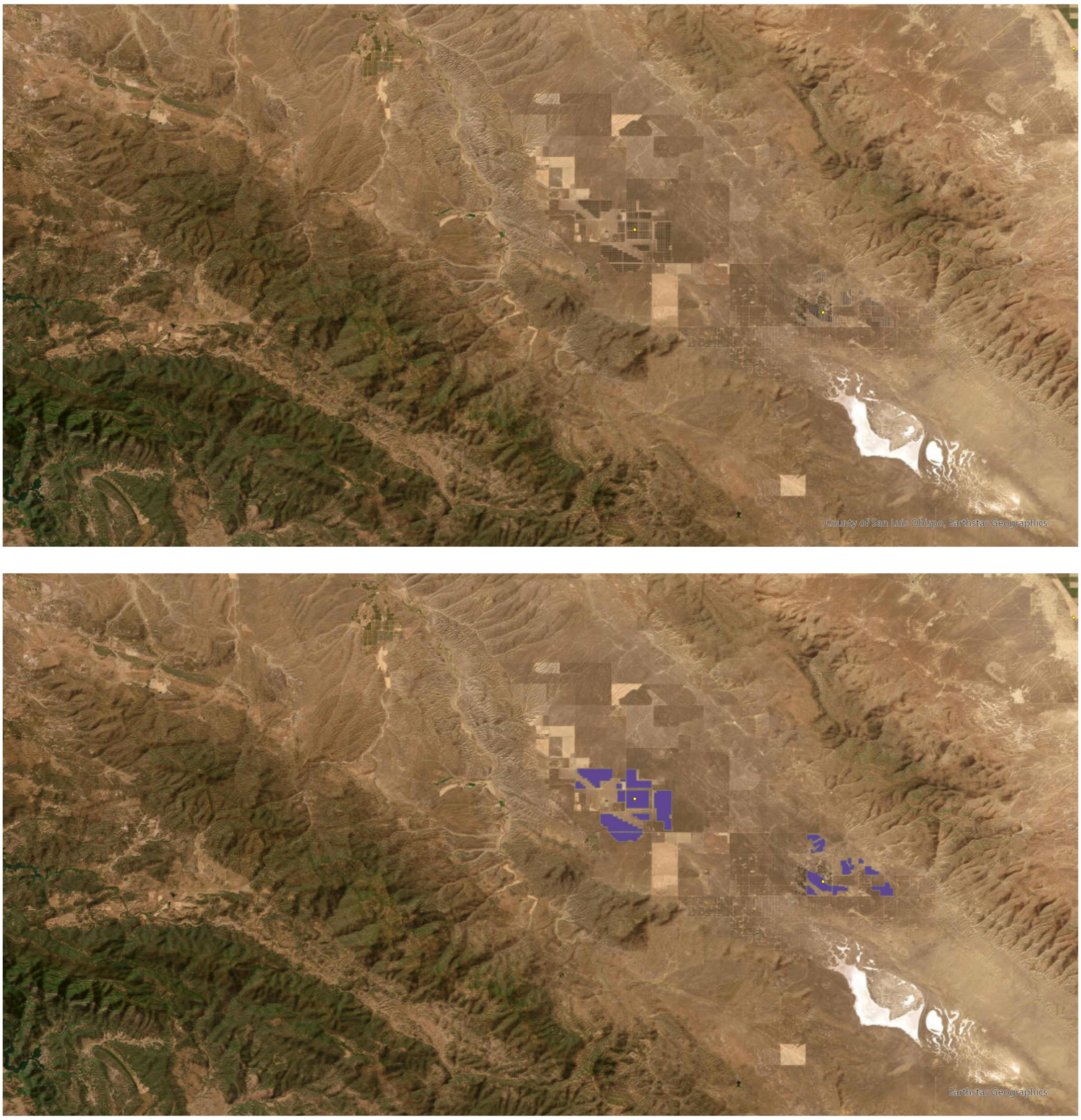


Figure IA 2: These figures illustrate the identification of a solar plant footprint using Sentinel-2 satellite data. The plant is the Topaz Solar Farm in California, U.S., with a capacity of 129 MW. The top picture shows the original satellite image. The bottom picture illustrates the plant detection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

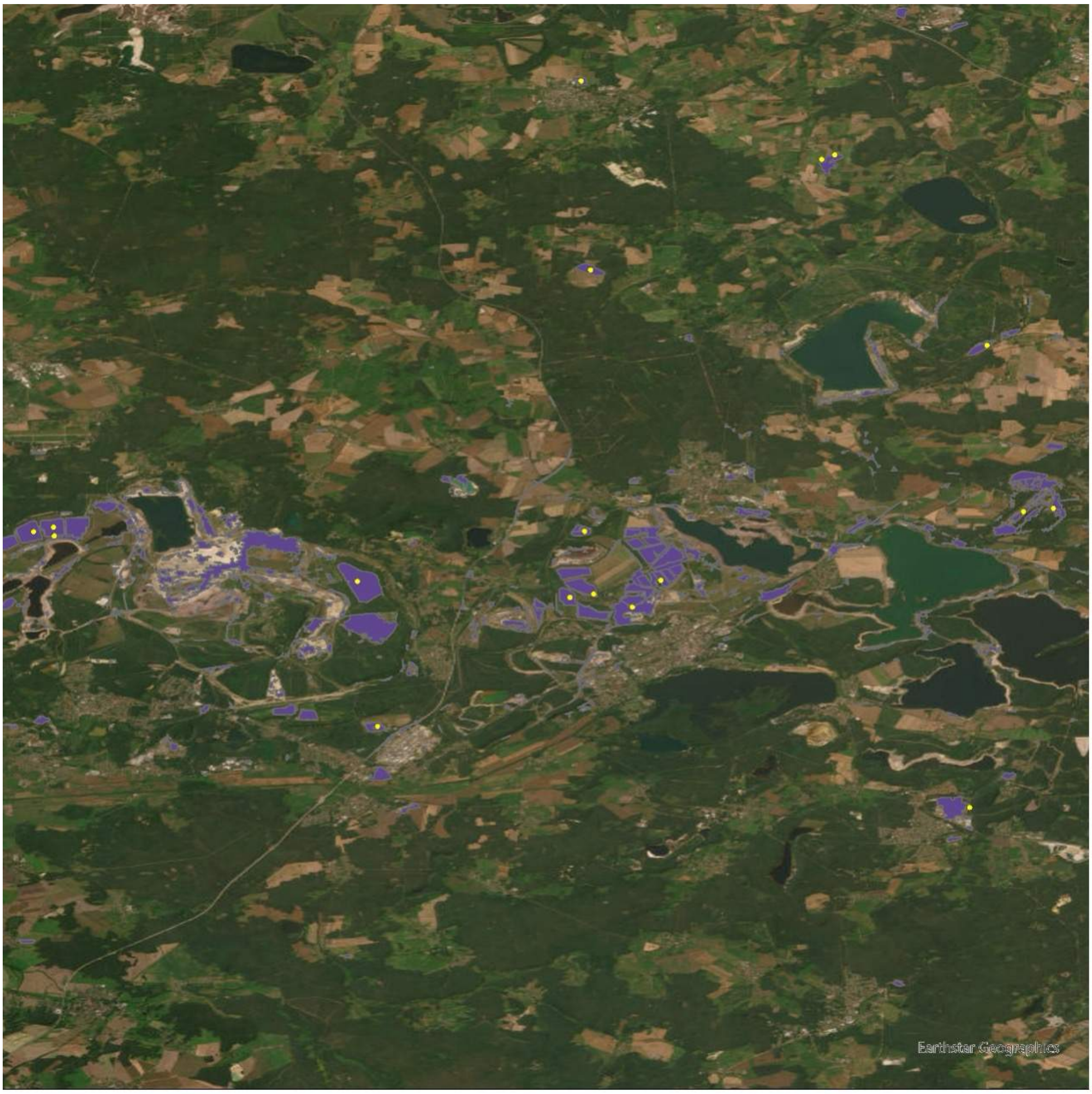


Figure IA 3: This figure shows the detected solar farm footprints near Königsberg, Germany. This example illustrates the methodology for handling clusters of plants, where total land use is calculated for closely-sited facilities and then allocated to individual plants based on their capacity.

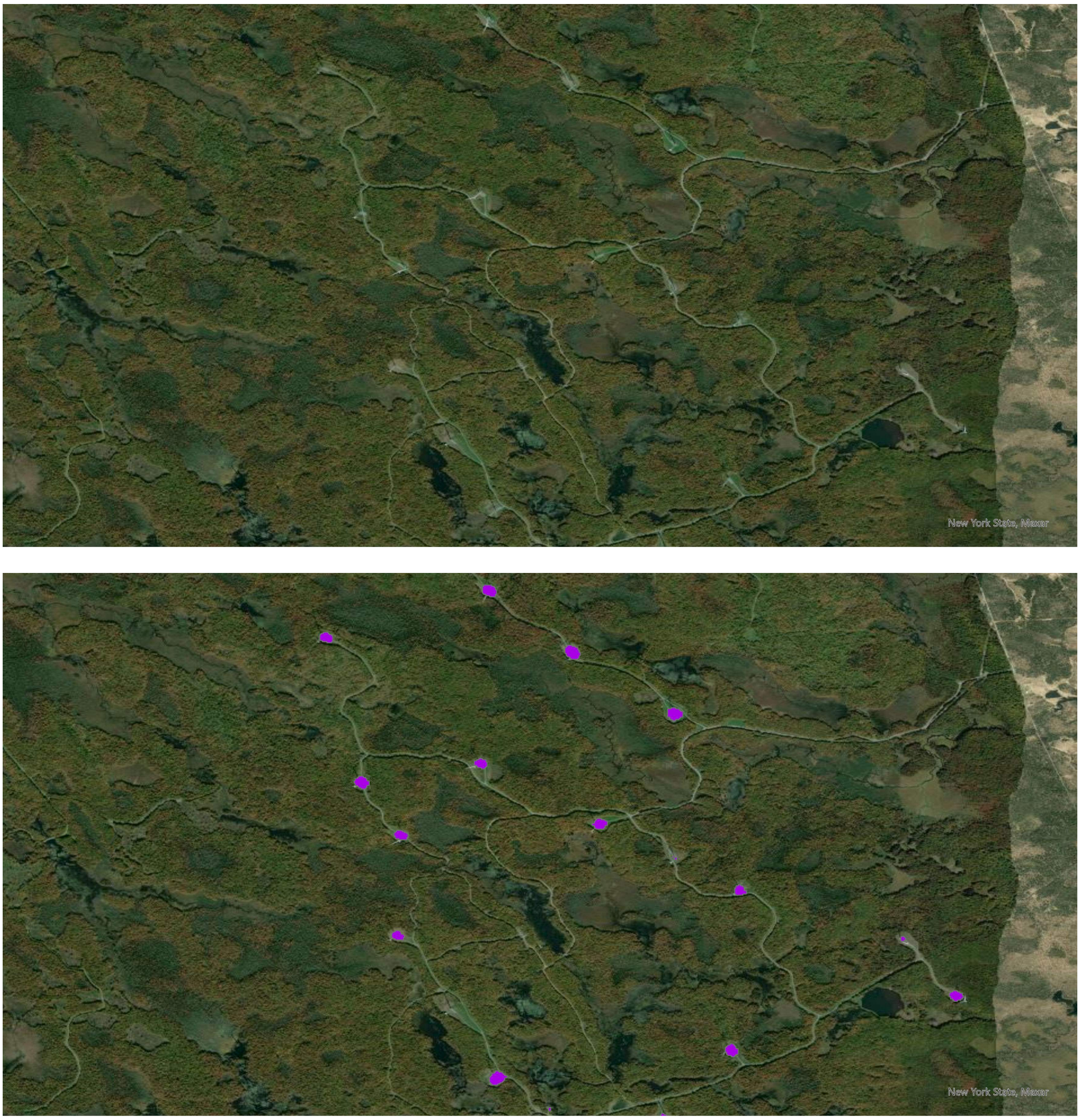
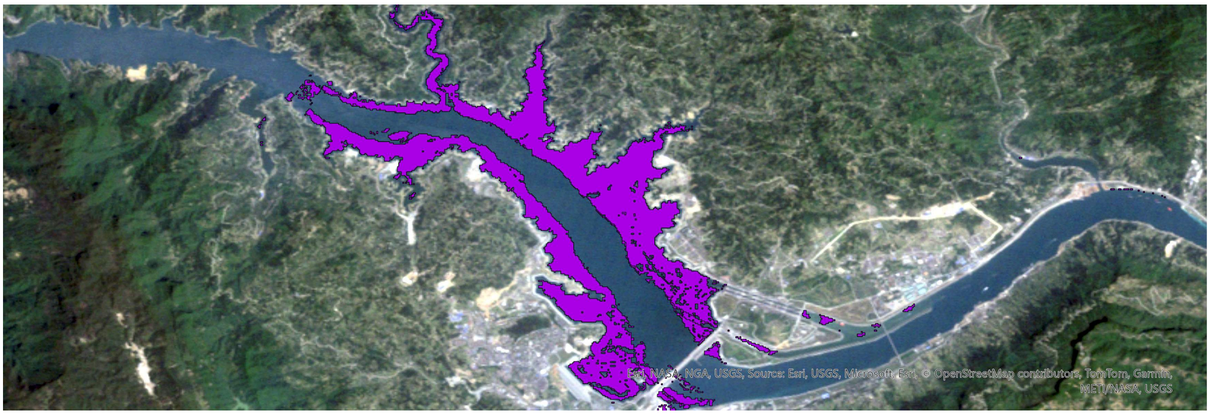


Figure IA 4: These figures illustrate the identification of a wind plant footprint using Sentinel-2 satellite data. The plant is the Roaring Brook Wind Farm in New York State, U.S., with a capacity of 79.7 MW. The top picture shows the original satellite image. The bottom picture illustrates the plant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

(a) original image - before dam construction

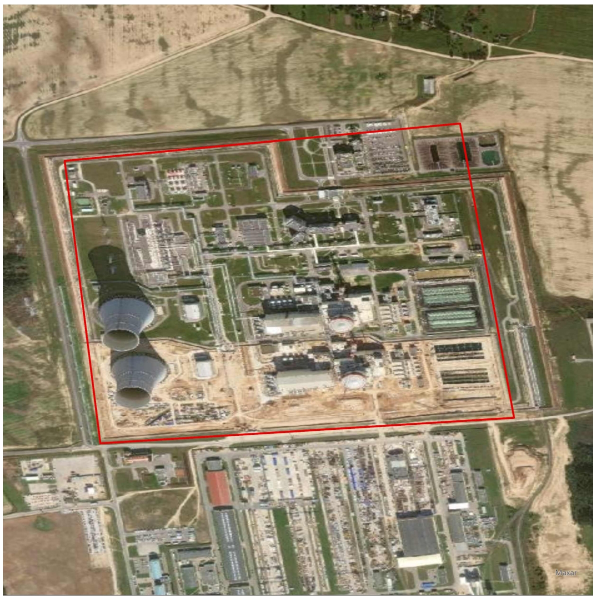
(b) original image - after dam construction



(c) plant detection algorithm

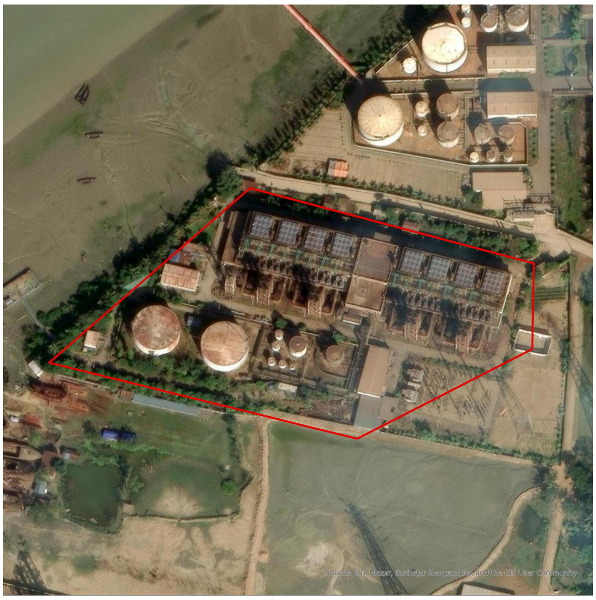
Figure IA 5: These figures illustrate the identification of a hydro plant footprint using Sentinel-2 satellite data. The plant is the Three Gorges Dam in China with a capacity of 22,820 MW. The top picture shows the original satellite image before the dam was constructed. The middle picture shows the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

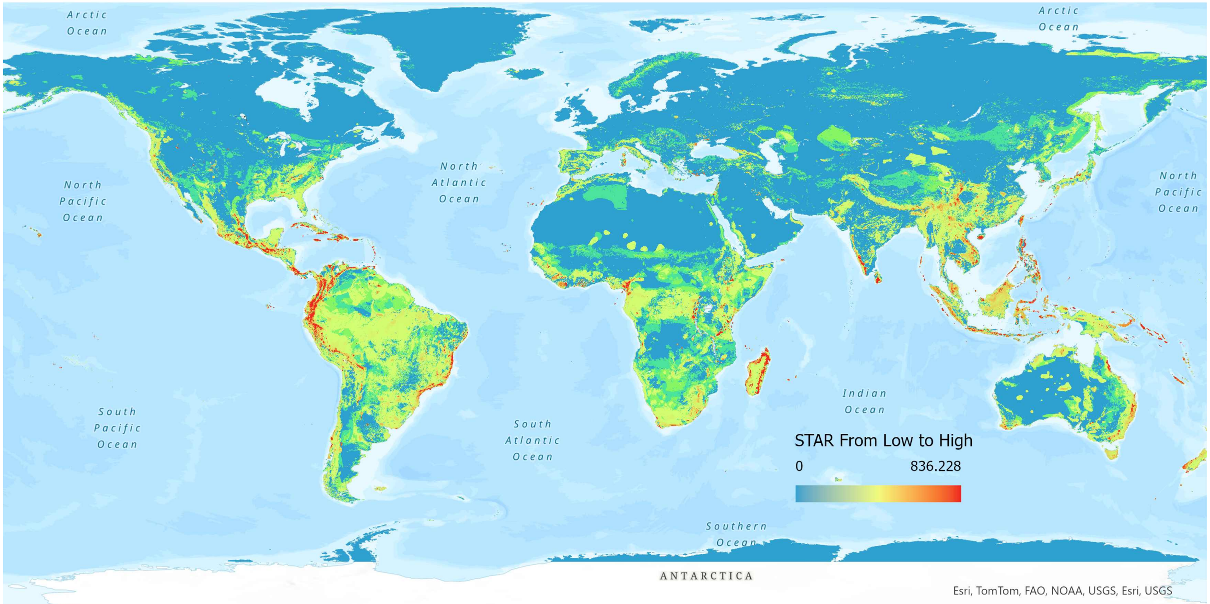


Figure IA 7: This figure illustrates the Species Threat Abatement (STAR$_T$) scores that we use to calculate the biodiversity impact of RE power plants. The STAR$_T$ score reflects the potential for conservation efforts in a specific area. The color indicates the STAR$_T$ score, with blue representing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

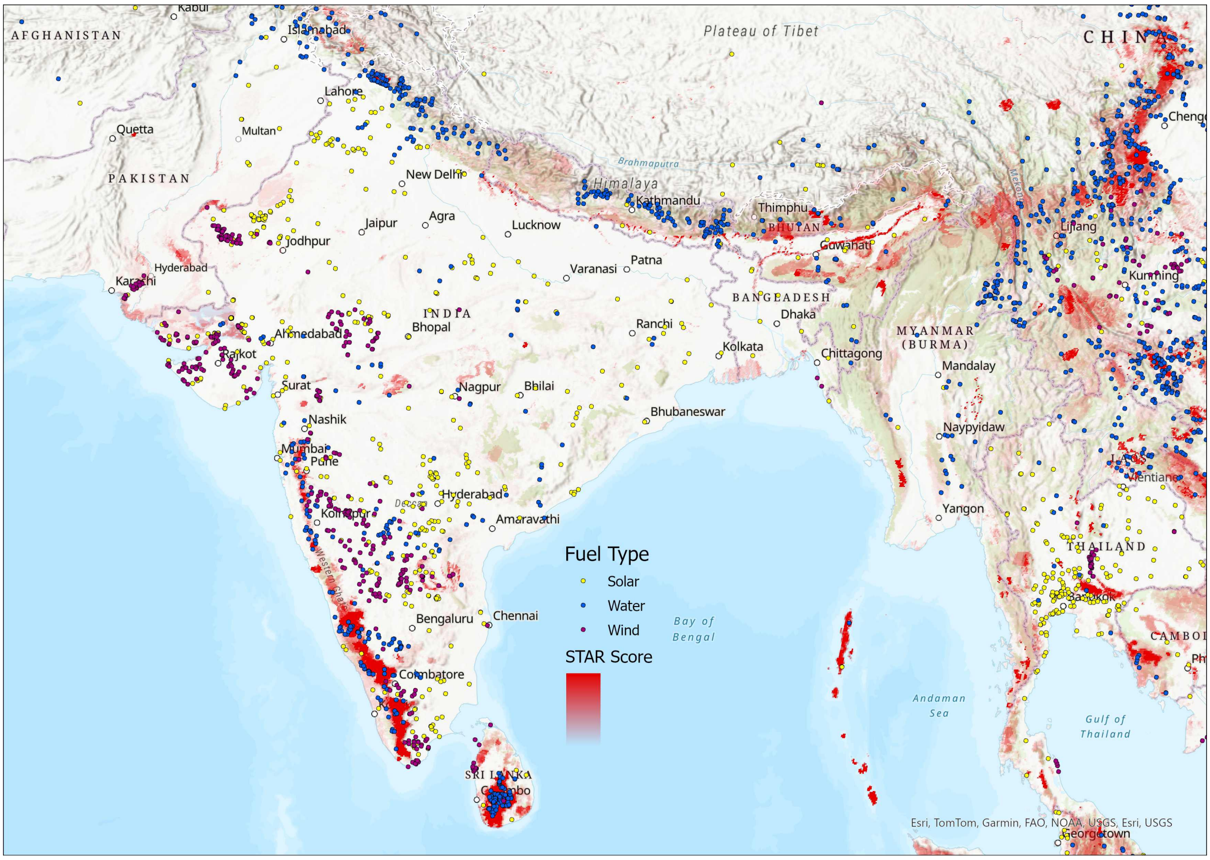


Figure IA 8: This figure illustrates the spatial relationship between RE power plants and STAR_T scores in South Asia. Solar plants are in yellow, wind plants in purple, and hydro plants in blue. Areas with high STAR_T scores are colored in red.

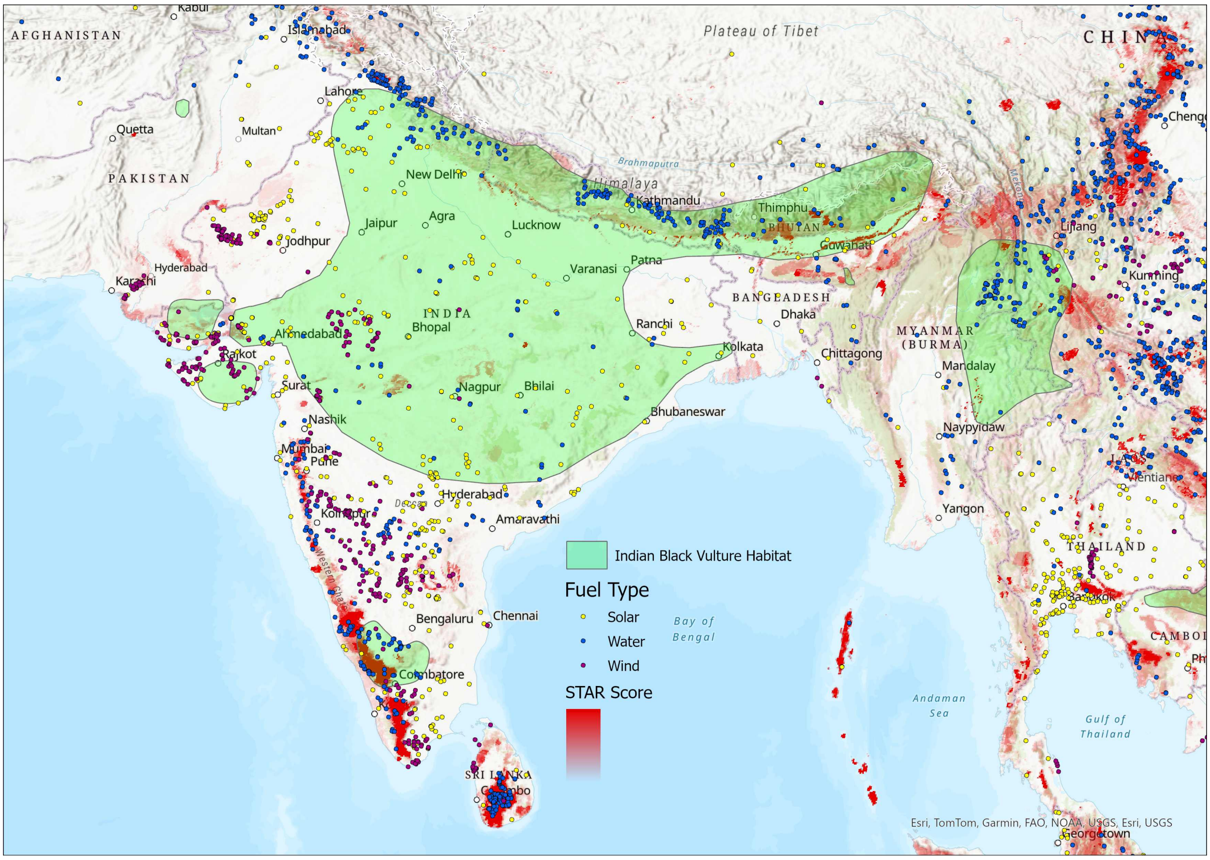


Figure IA 9: This figure illustrates the area of habitat for the Indian Black Vulture (*Sarcogyps calvus*) as well as the locations of RE power plants in South Asia.

Figure IA 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.

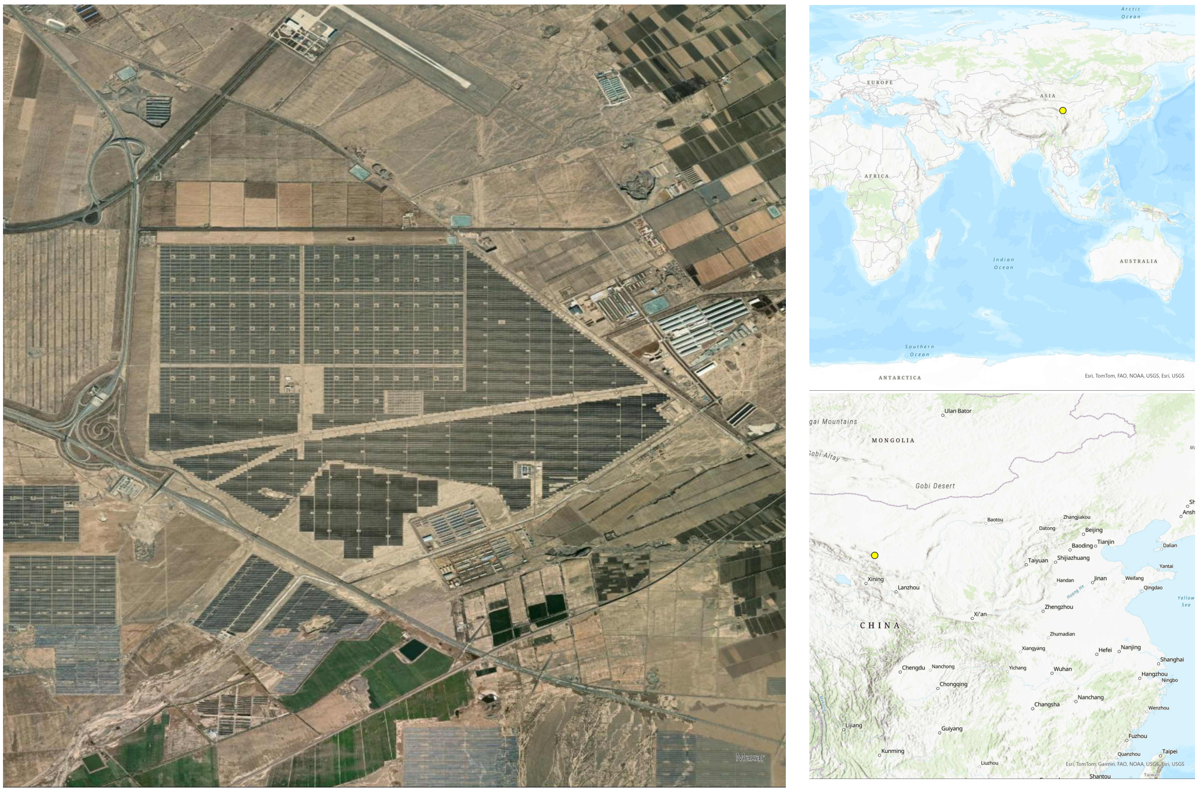


Figure IA 11: This figure illustrates the location of the Jinchang Jinchuan Solar Plant in the Gobi Desert. The picture on the left is a satellite image of the plant and the pictures on the right side are maps on which the location is highlighted with a yellow dot.

Table IA 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 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 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 4: Ownership Overview

	Direct		Ultimate	
Category	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.