DOI: 10.1111/jiec.70114

METHODS ARTICLE

JOURNAL OF INDUSTRIAL ECOLOGY WILEY

WindTrace

Assessing the environmental impacts of wind energy designs with a parametric life cycle inventory model

Miquel Sierra-Montoya[1] | **Joan Muñoz-Liesa**[2] | **Laura À. Pérez-Sánchez**[1] | **Alexander de Tomás-Pascual**[1] | **Cristina Madrid-López**[1,3]

[1]Institut de Ciència i Tecnologia Ambientals, Universitat Autònoma de Barcelona (UAB), Cerdanyola del Vallès, Barcelona, Spain

[2]Department of Sustainable Development, Environmental Sciences and Engineering (SEED), Royal Institute of Technology (KTH), Stockholm, Sweden

[3]Department/DIVISION: Centro de investigación Sociotécnica (CISOT), Centro de Investigaciones Energéticas, Medioambientales y Tecnológicas (CIEMAT), Cerdanyola del Vallès, Barcelona, Spain

Correspondence
Miquel Sierra-Montoya and Cristina Madrid-Lopez, Institut de Ciència i Tecnologia Ambientals, Universitat Autònoma de Barcelona (UAB), Campus UAB, C. de les Columnes, s/n. 08193 Bellaterra, Barcelona, Spain. Email: miquel.sierra@uab.cat and cristina.madrid@ciemat.es

Editor Managing Review: Nils Thonemann

Funding information
HORIZON EUROPE Climate, Energy and Mobility, Grant/Award Number: 101083936; Agencia Estatal de Investigación, Grant/Award Numbers: CEX2019-0940-M, PID2020-119565RJ-I00; Departament d'Innovació, Universitats i Empresa, Generalitat de Catalunya, Grant/Award Numbers: 2021 SGR 00734, 2024FI-100741; Svenska Forskningsrådet Formas, Grant/Award Number: 2022-02850

Abstract

Wind energy is expanding rapidly in Europe and plays a crucial role in the energy transition, yet existing life cycle inventory databases are outdated and lack the flexibility to accommodate continuously growing sizes of wind turbines. Here, we introduce WindTrace, an open-source parametric model built on Brightway that generates customized life cycle inventories for onshore wind turbines and parks. Fed by up-to-date data from literature and industry reports, the model uses 20 user-defined parameters, covering both turbine characteristics (e.g., hub height and power capacity) and wind park attributes (e.g., number of turbines and coordinates). Such parameters serve to unveil the influence of onshore wind turbines' design on their respective environmental impacts.

In this work, we first demonstrate WindTrace's advantages by comparing the differences in life cycle inventories and environmental impacts of 800 kW, 2 MW, and 4.5 MW wind turbines with their Ecoinvent counterparts. This is particularly true for 4.5 MW turbines, where differences in tower design, land use, and end-of-life assumptions cause 16× higher freshwater ecotoxicity, 2.2× higher climate change, and 1.6× lower land use impacts in Ecoinvent. By testing model parameters, we highlight that scaling up from 1990s turbines (700 kW; 60 m) to current average sizes (4.5 MW; 100 m) has reduced the turbines' climate change intensity by 38%. Furthermore, transitioning to future cleaner steel production could cut climate change impacts by 28%. Finally, increasing the European capacity factor from 24% to 35%, as suggested by WindEurope, reduces climate change impacts per kWh by 31.4%.

KEYWORDS
environmental impacts, industrial ecology, life cycle assessment, onshore turbines, parametric model, wind energy

1 INTRODUCTION

The European Union (EU) has set an ambitious target of 42.5% of its energy to be renewable by 2030. This will require expanding its installed wind power capacity (including both onshore and offshore turbines) to 500 gigawatts, roughly doubling the existing capacity (European Commission, 2023). Even though wind energy is a renewable energy source, the deployment of wind turbines is not environmentally harmless. Rather, it entails the consumption of raw materials, water, and energy during the manufacturing, installation, maintenance, and decommissioning processes.

Life cycle assessment (LCA) is a key framework in the evaluation of the environmental performance of energy technologies, including wind turbines. Nevertheless, a major challenge to perform wind turbine LCAs lies in the scarcity of updated, open, and accessible data (Arvesen & Hertwich, 2012; Mello et al., 2020; Mendecka & Lombardi, 2019; Price & Kendall, 2012). For example, datasets in GaBi represent 1.65 MW turbines, with data from 2011 (Kupfer et al., 2021). Alternatively, Ecoinvent contains turbines up to 4.5 MW based on reports published between 2003 and 2010, which, in turn, rely on primary data collected as far back as 1998 (Wernet et al., 2016). These datasets describe an instance of a turbine, with certain technical and technological specifications, and a geographical context. Therefore, they fail to represent today's or near-future turbines properly. First, they cannot capture current growing trends in Europe, where the average onshore turbine size scaled from 2.7 MW in 2017 to 4.5 MW in 2023 (WindEurope, 2019, 2024), nor technological improvements, which notably affect the material demands of the turbine. Second, they use constant values for crucial factors significantly influencing electricity production, such as capacity factor (CF) and lifetime (Li, Mogollón, Tukker, Dong, et al., 2022; Padey et al., 2013; Xu et al., 2023). These parameters are location-specific and are also improving with technological advancements. Consequently, these static datasets have a limited ability to assess whether the EU's wind energy expansion strategy aligns with broader sustainability objectives (Telsnig et al., 2022). In addition, they hinder the understanding of comprehensive environmental trade-offs of critical future EU technologies that depend on wind electricity, such as green hydrogen production, or industries like steel manufacturing (European Commission, 2020).

1.1 Existing parametrized life cycle inventory models for wind turbines

Parameterized life cycle inventory (LCI) models leverage data from literature or databases to generate customized life cycle inventories using specific technical parameters. They are increasingly adopted in the LCA field to bridge detailed micro-product descriptions (Hellweg & Milà Canals, 2014) with generalizable applications. This is evidenced by the development of dedicated frameworks such as *lca_algebraic* (Jolivet et al., 2021), already used to update inventories for solar photovoltaic systems (Besseau et al., 2023).

Table 1 summarizes the existing parametrized LCI models for wind in the literature. Initial attempts began in the early 2010s, when Blanc et al. (2012) proposed a model designed to provide environmental guidance for new offshore wind park projects in Northern Europe. They parametrized cabling, foundations, and transportation, but not the turbine itself, for which they relied on a single 5 MW dataset from literature. Zimmermann (2013) presented a tool built upon direct data gathered from industry but restricted to analyzing combinations of three Enercon turbine models

TABLE 1 Comparison of characteristics and parameters of currently available life cycle inventory (LCI) wind turbine parametrized models and the present paper.

	Blanc et al. (2012)	Zimmermann (2013)	Padey et al. (2013)	Li, Mogollón, Tukker, Dong, et al. (2022)	Sacchi et al. (2019)	WindTrace (this paper)
Scope	Offshore (only park, not turbine)	Onshore (only Enercon)	Onshore	Offshore	Onshore and Offshore	Onshore
Region of application	Northern Europe	Global	Europe	Global	Denmark	Europe
Open-source availability	No	No	No	No	Yes	Yes
Background adjustments	No	No	No	Prospective background databases	Time-adjusted electricity and steel (Danish context)	Geographically and time-adjusted steel
Data sources on material demands	Weinzettel and Kovanda (2009)	Primary data from Enercon	Different reports and literature	Different reports and literature	Burger and Bauer (2007)	Vestas reports (2014–2023) and Sacchi et al. (2019)
Power range and number of turbine datasets	5 MW 1 dataset	2–2.3 MW 7 datasets	22 datasets	–	30 kW–2 MW 6 datasets	150 kW–6.2 MW 24 datasets

with four possible tower types. Finally, Padey et al. (2013) proposed a simplified model to provide life cycle greenhouse gas emissions per kWh of wind energy.

Later attempts were complete and more robust and included advanced LCA capabilities such as time and geographical adaptation of the database background. Li, Mogollón, Tukker, Dong, et al. (2022) proposed a material flow analysis model to explore the material requirements for an offshore wind turbine. It allows building a turbine by choosing among different component technologies in a puzzle-like approach. This study evolved into a complete LCA model, including all life cycle stages, and allowed the use of prospective background databases from premise (Sacchi et al., 2022) for future offshore wind implementation scenarios (Li, Mogollón, Tukker, & Steubing (2022). Nevertheless, the model is not open-source, and it uses constant material intensities per MW, overlooking possible material efficiency gains from scaling up to bigger turbines (Caduff et al., 2012).

Finally, Sacchi et al. (2019) presented an open-source model that encompasses onshore and offshore turbines. It was later applied to assess the environmental footprint of Denmark's wind fleet (Besseau et al., 2019), and eventually evolved into an open-source Python package named windisch (Sacchi, 2021). The model builds on data from six sets of discrete turbines, and upscales the material demands with a great level of detail (e.g., materials in the bed frame within the nacelle). Moreover, it adjusts the LCA background to the Danish context for electricity, heat, non-ferrous metals, and plastics markets geographically, and also electricity and steel, with national time series data. However, the primary limitation arises from the dataset sources used to determine material demands, which rely on a 2007 report featuring data from turbines ranging between 30 kW and 2 MW. This limits the potential of the tool to build reliable inventories for current or near-future turbines, which in 2023 are 4.5 MW on average (WindEurope, 2024). Finally, despite being open source, it does not come with detailed guidelines and examples to easily apply its functionalities.

1.2 | Contribution and novelty

In this work, we introduce WindTrace, a parametric LCI model that allows building tailor-made life cycle inventories for onshore wind turbines and parks in Europe using a set of user-defined parameters (see source code in Sierra-Montoya, 2024). It is implemented in a Python module, building on the LCA framework Brightway 2.5 (Mutel, 2017). The main contribution of WindTrace is to provide life cycle inventories using a broad and up-to-date wind technology data used in its foundations, compared to existing databases and tools. The material inputs of the turbine are derived from 24 datasets, four dating back to 2007 and the rest spanning the 2014–2023 period, covering a power range from 150 kW to 6.2 MW. Its detailed cradle-to-gate life cycle stages coverage, combined with 20 customizable input parameters, enhances its flexibility and adaptability to a wide range of scenarios and settings. This fills a gap by offering a flexible tool for current and future turbine modeling. Moreover, WindTrace serves as a useful screening tool in the early phases of the eco-design process, where key technical decisions are made but detailed product specifications are not yet available (ISO14006:2020). Its strength lies in supporting strategic choices at a point in the process where decisions can still significantly influence the sustainability of the final product. The tool is openly available at Zenodo (Sierra-Montoya, 2024) and GitHub, with examples on how to use it in a Jupyter Notebook.

After explaining the design of the WindTrace model in Section 2, we investigate in Section 3 how our approach improves upon static Ecoinvent inventories, focusing on climate change, freshwater ecotoxicity, and land use impact categories. In Section 4, we complete a study of sensitive parameters in the environmental performance of wind turbines, with emphasis on climate change impacts. This analysis sheds light on the complexity of wind energy environmental assessments, overlooked in static turbine representations. It also identifies opportunities to reduce the environmental footprint of wind turbines, supporting more informed decision-making. Finally, in Section 5, we highlight the contributions of the study.

2 | METHODS

2.1 | WindTrace overview and inputs

Figure 1 shows the schematic representation of WindTrace's workflow. It requires 20 input parameters introduced by the user (Table 1 of Supporting Information S1). Ten parameters must be defined based on user needs, whereas the other 10 parameters are optional, as WindTrace has predefined default values in case the user lacks specific information. The inputs are combined with up-to-date technical data from the literature and industry reports to build an LCI. The outputs include the LCIs of: (1) the wind park, constituted by the number of wind turbines, the intra-array cables, and the transformer; and (2) a single wind turbine, including its materials, manufacturing, transport, installation, maintenance, and end-of-life. Both outputs can be obtained per unit of infrastructure (e.g., 1× wind turbine and 1× wind park) and per kWh of electricity produced.

2.2 | LCI modeling approach

In this section, we will describe the system boundaries, data sources, and assumptions to build the LCI foreground of the wind turbines and park. For background data, we employed Ecoinvent v3.9.1 (Wernet et al., 2016) using the cut-off system model. However, compatibility with versions 3.10

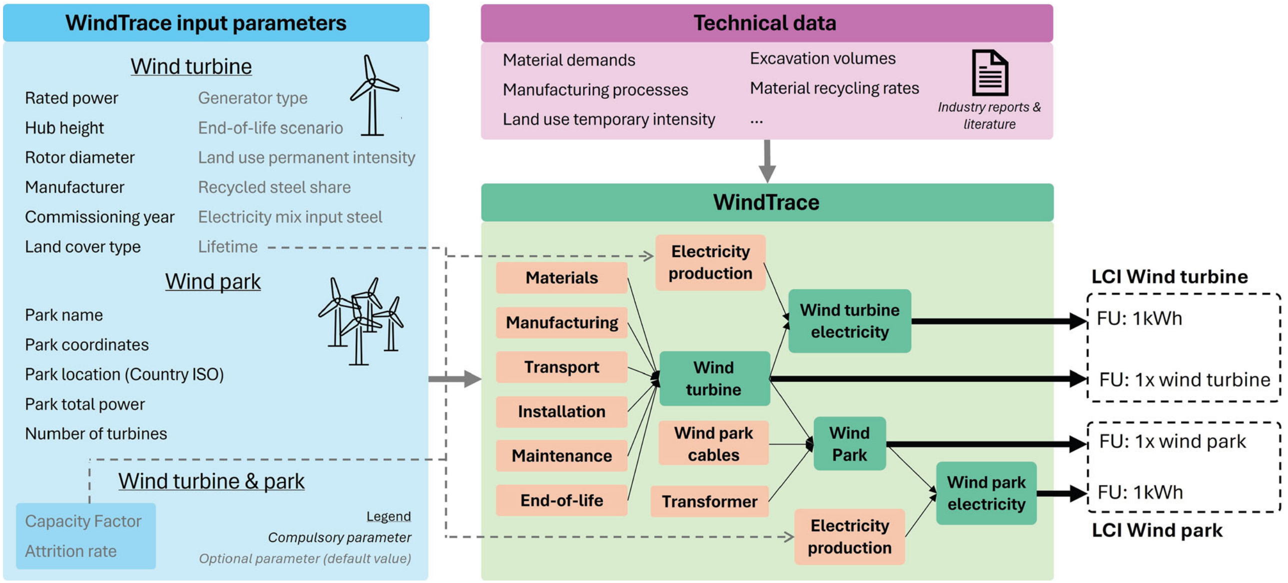

FIGURE 1 Scheme of the WindTrace's workflow. Gray arrows correspond to input data, and black arrows are outputs. The blue boxes define the input parameters introduced by the user. The purple box lists the technical data we used to build WindTrace. FU, functional unit; LCI, life cycle inventory.

and 3.10.1 is also granted. Further details on WindTrace's development process and its validation can be found in Supporting Information S1 and S2.

2.2.1 | Wind turbines

Material demands

Materials from the turbine and the foundations were modeled using data from 21 Vestas turbines (2–6.2 MW), sourced from Vestas LCA reports from the period 2011–2023 (Section 1.1.1 of Supporting Information S1). Additional data from three smaller turbines (150–800 kW) were incorporated from Sacchi et al. (2019). Turbine material inputs were modeled by fitting the mass of each aggregated material to turbine capacity, except for steel, which was fitted to hub height or D^2h (see Figure 1 of Supporting Information S1). Normal distributions were used for all fitting curves except steel, where a uniform distribution was applied (Section 1.1.1.2 of Supporting Information S1). Mean standard deviations of material masses were stored in the inventory to represent uncertainty.

Although rare earth elements are absent from the reference data, meeting future wind industry demands poses a major challenge (Alves Dias et al., 2020; Li et al., 2020). Therefore, WindTrace includes material intensities for praseodymium, neodymium, dysprosium, terbium, and boron depending on the type of generator used (Carrara et al., 2020). Details on material types, data collection process, allocations, and selected background activities are detailed in Section 1.1 of Supporting Information S1.

Steel, primarily used in the tower, is the heaviest material in a wind turbine (54%–71% by mass, excluding foundations, according to Vestas reports). Europe produced 126 Mt of steel in 2023 and has only been a net importer since 2016 (Eurofer, 2024). Thus, WindTrace adapts the steel background activity to assume entirely European production, accounting for primary and secondary steel shares (56.4%–59.5%) with geographical and temporal resolution (2012–2021).

Manufacturing and transportation

The manufacturing stage covers the industrial processes shaping wind turbine materials, each linked to an Ecoinvent process (Table 6 of Supporting Information S1). It also includes electricity use in the nacelle assembly. To ensure geographic specificity, European manufacturing sites (Vestas, Siemens Gamesa, Nordex, Enercon, LM Wind) were identified from official sources. The nearest factory location determines transportation distance to the wind farm and the national electricity mix for manufacturing. For simplicity, a single manufacturing site for all components and straight-line road transport are assumed.

Installation

The installation stage includes the temporary and permanent land transformation due to the deployment of the access roads, the substation, the transformer, and the turbines, according to land use shares provided by Denholm et al. (2009). Since these data are provided at the wind farm level, we attribute the corresponding land-use intensity per unit of capacity to individual turbines.

It also includes the excavation activities to set the turbine foundations and the construction of the access roads.

Maintenance

The maintenance stage includes inspection trips every 6 months (Elsam Engineering, 2004) and lubricating oil changes every 2 years (Abeliotis & Pactiti, 2014). The replacement of turbine sub-components during their operational lifetime is excluded from the system boundaries due to their highly case-specific nature, being too unpredictable to be generalized.

End-of-life

We followed a cut-off system model approach, considering no environmental burdens related to recycling processes (Figure 8 of Supporting Information S1), as these are allocated to the user of the recycled material (Sonderegger & Stoikou, 2022). Four end-of-life scenarios can be selected in WindTrace (further details in Section 1.4 of Supporting Information S1).

Wind turbine electricity production

The annual electricity production of a wind turbine depends on the annual capacity factor, which measures the electricity output of a turbine relative to its maximum electricity output at full capacity. However, as the turbine gets older, its efficiency is reduced due to physical attrition of turbine components, affecting its capacity factor (Germer & Kleidon, 2019; Olauson et al., 2017; Staffell & Green, 2014). WindTrace calculates the lifetime electricity production of a wind turbine using the initial annual CF provided by the user as input. It adjusts this CF over time based on an attrition rate, also specified by the user, to account for performance degradation. The resulting time-dependent CF is applied over the turbine's operational lifetime (Equation 1), where CF is the annual capacity factor, CF_i is the capacity factor of the first year, k is the attrition rate, and *age* is the operation year. Considering this, the electricity production of a turbine (E_{turbine}) is defined as the sum of the annual electricity production of a turbine of a certain power (P_{turbine}) throughout its operation lifetime (LT) as expressed in (Equation 2).

$$\text{CF} = \text{CF}_i \times (1-k)^{\text{age}} \tag{1}$$

$$E_{\text{turbine}} = P_{\text{turbine}} \times \text{Annual total hours} \times \text{CF}_i \sum_{0}^{\text{LT}-1} (1-k)^{\text{age}} \tag{2}$$

2.2.2 | Wind park

The wind park inventory contains the wind turbines, the intra-array cables, and the transformer. The system boundaries of the park are set at the transformer. The cables are modeled considering the materials, manufacturing process, and excavation activities. The transformer is modeled, scaling an ABB transformer of 500 MVA, including its materials, electricity, and heat requirements (ABB, 2003). Data sources and assumptions for cables and transformers are detailed in Section 1.5 of Supporting Information S1. The wind park power (P_{park}) serves to calculate the electricity production of a wind park (E_{park}; Equation 3).

$$E_{\text{park}} = P_{\text{park}} \times \text{Annual total hours} \times \text{CF}_i \sum_{0}^{\text{LT}-1} (1-k)^{\text{age}} \tag{3}$$

2.3 | Model validation

For validation purposes, we compared the Life Cycle Impact Assessment (LCIA) results of 18 Vestas turbines modeled using WindTrace against data from the original Vestas reports. The comparison was evaluated using root mean squared error, mean percentage error, and R^2, with results presented in Figures 5 and 7 of Supporting Information S1. Additionally, we assessed the material phase separately by conducting a Monte Carlo analysis on a reference turbine, comparing the static LCIA result with the upper and lower confidence intervals. Further details are in Section 2 of Supporting Information S1.

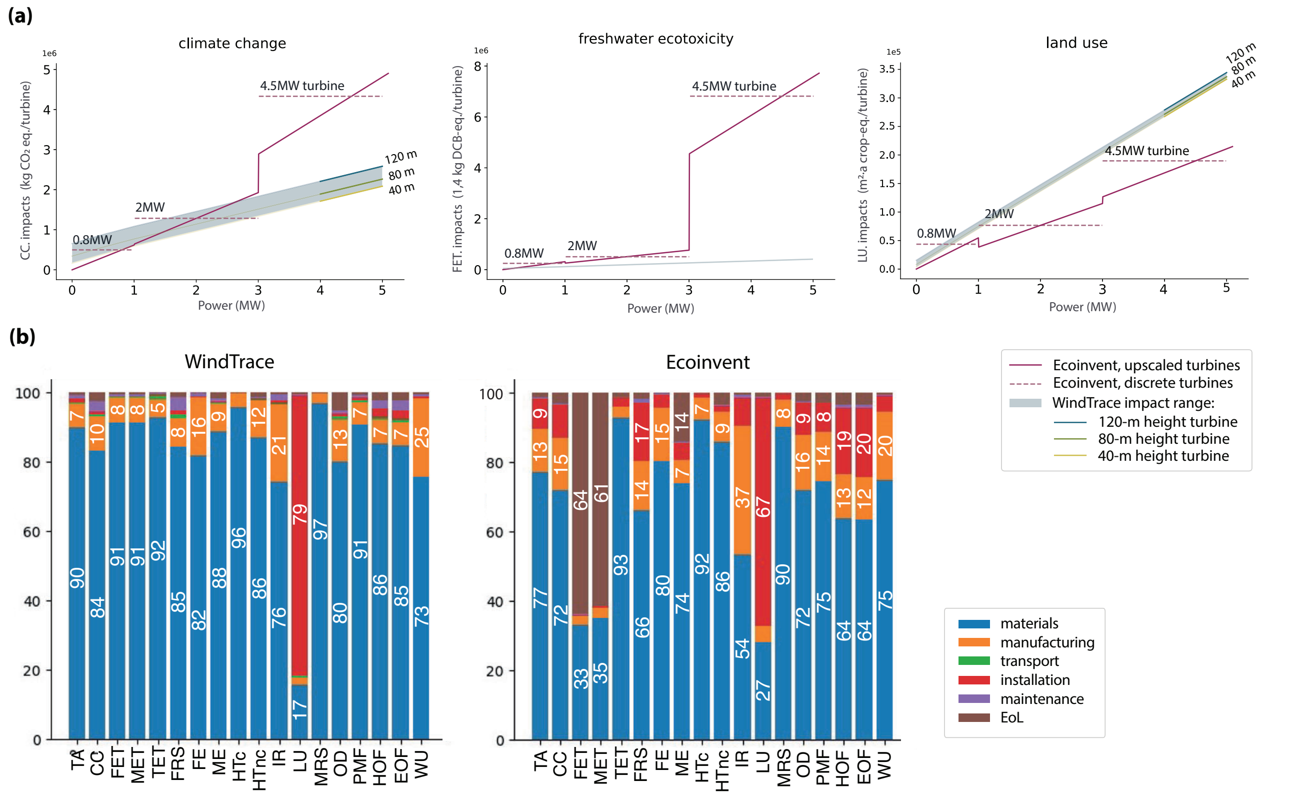

FIGURE 2 (a) Climate change, freshwater ecotoxicity, and land use results for Ecoinvent (purple) and WindTrace (gray) life cycle inventories (LCIs) in the 0–5 MW range. (b) Contribution analysis by life cycle phase of Vestas V80/2.0 modeled in WindTrace (left) and Ecoinvent (right). TA, terrestrial acidification; CC, climate change; FET, freshwater ecotoxicity; MET, marine ecotoxicity; TET, terrestrial ecotoxicity; FRS, fossil resource scarcity; FE, freshwater eutrophication; ME, marine eutrophication; HTc, human toxicity: cancer; HTnc, human toxicity: non-cancer; IR, ionizing radiation; LU, land use; MRS, mineral resource scarcity; OD, ozone depletion; PMF, fine particulate matter formation; HOF, photochemical oxidant formation: human health; EOF, photochemical oxidant formation: ecosystems quality; WU, water use. The underlying data for this figure are provided in the "Figure 2a" and "Figure 2b" sheets of Supporting Information S3.

3 | COMPARISON OF WINDTRACE AND ECOINVENT INVENTORIES

3.1 | Definition of a reference turbine and LCIA parameters

We defined a reference turbine (Vestas V90/2.0), which is the most installed onshore turbine in Europe up to 2021 (Pierrot, 2021). Its parameters are detailed in Table 15 of Supporting Information S1, which also summarizes how we varied these parameters both for their application in Sections 3 and 4.

We used Brightway 2.5 (v1.0.6) to calculate the LCIA results presented in the following sections. The impact assessment was performed with the ReCiPe 2016 v1.1 midpoint (H) method (Huijbregts et al., 2017). We focused mainly on the climate change impact indicator for simplification purposes, unless otherwise specified.

3.2 | LCIA comparison for 0–5 MW turbines

In this section, we compare WindTrace inventories to Ecoinvent's to highlight differences and showcase the advantages of our model. For this comparison, we used Ecoinvent's inventories for the 800 kW (Nordex N50/800), 2 MW (Vestas V80/2.0), and 4.5 MW (Enercon E-112) turbines to represent the 0–1, 1–3, and 3–5 MW ranges, respectively. In contrast, WindTrace was applied using the reference turbine parameters from Table 15 of Supporting Information S1, analyzing power outputs from 0 to 5 MW and hub heights of 40, 80, and 120 m, capturing the trend of towers to grow with increasing capacity (method details and limitations in Section 3.1 of Supporting Information S1).

In the 0–3 MW range, climate change impacts in Ecoinvent increase more steeply (660 tons CO_{2eq}/MW) compared to WindTrace (≈500 tons CO_{2eq}/MW) (Figure 2a). The most significant difference, however, appears in the 3–5 MW range, where Ecoinvent's impacts are up to 2.2 times higher. This discrepancy arises because Ecoinvent models a concrete tower instead of a steel one, resulting in 18% higher emissions than WindTrace's tower. Although concrete towers are used in some turbines, their adoption is rare, whereas steel towers remain the dominant and widely preferred solution (Stehly et al., 2024).

For freshwater ecotoxicity, Ecoinvent's impacts are up to 1.5 times higher for 2 MW turbines and 16 times higher for 4.5 MW turbines. This difference stems from Ecoinvent assuming 100% incineration for copper at the end-of-life, whereas WindTrace accounts for 90% recycling and 10% landfill (see Section 1.4 of Supporting Information S1). Regarding land use, WindTrace applies higher land transformation intensities (10,000 m^2/MW across all capacities by default; see Section 1.3.1 of Supporting Information S1) compared to Ecoinvent (69.8–1,400 m^2/MW), leading to consistently higher impacts in the 0–5 MW range (see Section 1.3 of Supporting Information S1).

3.3 | Contribution analysis of Vestas V80/2.0

The material phase is the dominant contributor across nearly all impact categories for both Vestas V80/2.0 turbine inventories modeled with WindTrace and Ecoinvent (Figure 2b). For WindTrace, materials account for 73.2% to 96.9% of impacts in all categories except land use, where installation dominates with 79.0% due to land transformation for turbine erection and supporting infrastructure. Ecoinvent's results also highlight the dominance of the materials phase, contributing between 54% and 93% of impacts, except for land use and marine and freshwater ecotoxicities. However, its material contributions are lower than in WindTrace, as Ecoinvent attributes higher impacts to the installation phase. This is due to Ecoinvent's inventory including 8.4 times more m*year of access roads and assuming they are asphalted, whereas WindTrace considers rural paths (Section 1.3.2 of Supporting Information S1). The discrepancy in marine and freshwater ecotoxicity stems from differences in end-of-life modeling as explained in Section 3.1. Maintenance impacts remain negligible in both models. Although Ecoinvent does not include transport, this does not affect the comparison, as WindTrace also shows minimal transport impacts. Comparison for 800 kW and 4.5 MW turbines is also provided in Figure 11 of Supporting Information S1, as well as method details in Section 3 of Supporting Information S1.

4 | INFLUENCE OF SENSITIVE PARAMETERS ON THE ENVIRONMENTAL IMPACTS OF WIND TURBINES

4.1 | Identification of sensitive parameters

This section synthesizes the theoretical relevance of five key parameters identified in the literature as influential in the environmental assessment of wind energy.

4.1.1 | Turbine power

LCA faces the challenge of linearity, meaning that doubling the demand for the same system product results in doubled environmental impacts (Guinée et al., 2011). However, this linearity does not hold for scalable technologies, where economies of scale can reduce the material footprint and the environmental impact (Pizzol et al., 2021). Scalability in wind energy has been discussed in previous works, showing that environmental impacts per kWh decrease with turbine size (Caduff et al., 2014), but its role per MW has barely been addressed before.

4.1.2 | Steel production process

Steel production in Europe is carbon-intensive, with emissions in 2018 ranging from 1.3 kg CO_{2eq}/kg_{steel} (BloombergNEF, 2021; Holappa, 2020) to 1.5 kg CO_{2eq}/kg_{steel} in our European adaptation of Ecoinvent. The dominant primary steel route, blast oxygen furnace (BOF), emits ~2.2 kg CO_{2eq}/kg_{steel} globally, while secondary steel via electric arc furnace (EAF) emits ~0.3 kg CO_{2eq}/kg_{steel}, depending on the electricity mix (Institute for Energy Economics & Financial Analysis, 2022). Thus, increasing secondary steel production (now at a constant ~42% since 2011 (Eurofer, 2022)) and renewable energy use would lower future emissions (International Energy Agency, 2020), crucial for wind turbines, where steel is the primary material by mass (excluding foundations).

4.1.3 | Generator types

Rare earth elements are key for wind turbine generator magnets. Gearbox designs, less reliant on rare earths, dominate the onshore turbines market (Alves Dias et al., 2020; Verma et al., 2022), while gearless direct-drive trains, more rare earth abundant, are leading in offshore due to easier

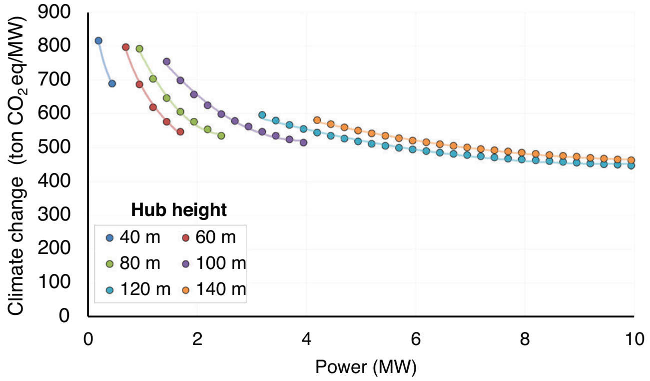

FIGURE 3 WindTrace results of climate change intensity (ton CO_{2eq}/MW) per turbine power for hub heights from 40 to 140 m. The underlying data for this figure are provided in the "Figure 3" sheet of Supporting Information S3.

maintenance (Depraiter & Goutte, 2023). Many wind turbine LCAs exclude rare earths due to 0.1%–1% cut-off criteria (Vestas, 2015). However, rare earth mining releases nitrogen into water (Shu et al., 2024) and often involves extracting radioactive materials, leading to radiation exposure during mining and processing (Bittner et al., 2023). Moreover, their ore concentration is decreasing faster than that of other metals such as copper (Gschneidner & Pecharsky, 2024).

4.1.4 | Lifetime

Lifetime strongly affects the electricity production of a turbine, thus influencing its environmental impact per kWh. LCAs typically assume 20 years for onshore turbines (Arvesen & Hertwich, 2012; Vestas, 2022), though actual lifetimes vary. Decommissioned turbines in Denmark (1977–2016) averaged 18.4 years (Sacchi et al., 2019), while those in Europe decommissioned by 2020 averaged 18.9 years (Figure 16 of Supporting Information S1). Nevertheless, some have been running for over 45 years (Tvindkraft, n.d.), and new turbines, especially offshore, are expected to last at least 30 years (Vestas, 2024).

4.1.5 | Capacity factor

CF depends on wind availability, hub height, and turbine technology (Jung & Schindler, 2023; Xu et al., 2023). Wind availability influences how often and how efficiently a turbine can generate power, while hub height modulates access to laminar flows. Furthermore, new technologies tend to have improved power curves, meaning enhanced conversion of wind to power output. Given the intricate interplay of these drivers, CFs vary widely among locations. However, the global 3-year mean CF rose from 0.22 to 0.25 in the period 2010–2012 to 2018–2020 (Jung & Schindler, 2023), while the European onshore mean is expected to rise from 0.24 of the current fleet to 0.30–0.35 for new installations (WindEurope, 2024).

4.2 | Environmental assessment of turbine parameters

4.2.1 | Power and hub height

To explore potential economies of scale in wind turbines, this section assesses the relationship between climate change impacts and turbine power. Figure 3 shows an exponential decline in impact intensity (ton CO_{2eq}/MW) with power, meaning that the marginal reduction diminishes as capacity grows. A similar trend was observed by Sacchi et al. (2019) for Danish turbines ranging from 100 to 500 kW, though their study did not find the same intensity decay trend for larger turbines. In contrast, Mendecka and Lombardi (2019) reported a consistent exponential decrease across the entire 0–3 MW range in their harmonized LCA model.

Here, we modeled steel demand as a function of hub height, while all other material demands are a function of power. This makes the hub height-to-power ratio a key factor in determining environmental impacts. When turbine power increases without changing hub height, the total embodied material mass per MW decreases, as the relative share of steel is reduced. This results in lower climate change intensity per unit of power. Empirical data from turbines installed in Europe until 2021 (Pierrot, 2021) show that the hub height-to-power ratio declines exponentially with increasing

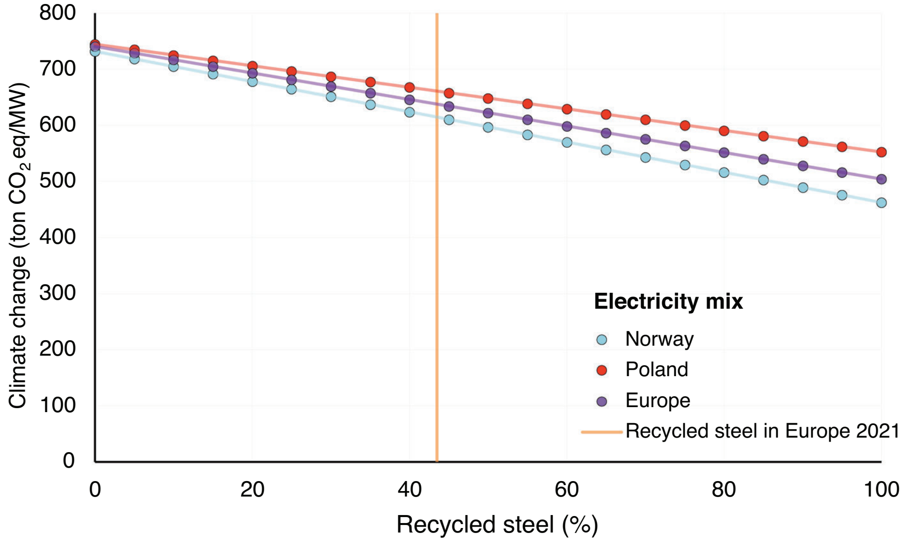

FIGURE 4 Climate change impacts per turbine according to the share of recycled steel and electricity mix (Norway, Poland, or Europe). Recycled steel in Europe in 2021 from Eurofer (2022). The underlying data for this figure are provided in the "Figure 4" sheet of Supporting Information S3.

power (Figure 14 of Supporting Information S1), from 0.235 m/kW for 100 kW turbines to 0.012 m/kW for 12 MW turbines. This confirms that bigger turbines tend to have less embodied material.

This finding underscores the economies of scale in wind turbine design, where increasing nominal power improves material efficiency (Beiter et al., 2022; Sieros et al., 2012). For example, scaling up from a typical 1990s turbine (700 kW and 60 m height) to the 2023 average (4.5 MW and 100 m height) has reduced the climate change intensity per MW by 38%, primarily due to a lower total embodied mass per unit of power. The same behavior occurs for other LCIA indicators (Figure 15 of Supporting Information S1).

4.2.2 | Steel production

Steel accounts for 36.2% of the climate change impacts of the reference turbine in WindTrace which, combined with chromium steel, increases to 48.7% (Table 16 of Supporting Information S1). Given this significant contribution, we evaluated the influence of steel recycling rates (0%–100%) and the electricity mix in steel production on the climate change impacts of a turbine. To capture a range of carbon intensities, we selected the 2019 electricity mixes of Poland, Europe, and Norway, representing the highest (0.95 kg CO_2eq/kWh, Poland), average (0.35 kg CO_2eq/kWh, Europe), and lowest (0.024 kg CO_2eq/kWh, Norway) carbon-intensive grids in Europe (Ecoinvent). These electricity mixes were applied to both BOF and EAF production of steel and chromium steel.

Figure 4 shows there is a 38% difference in climate change impacts between the worst-case scenario (0% recycled steel and Poland's electricity mix; 744 tons CO_{2eq}/MW) and the best-case scenario (100% recycled steel and Norway's electricity mix; 462 tons CO_{2eq}/MW).

Assuming a scenario with 100% recycled steel without altering the electricity mix, the climate change impacts of the wind turbine decrease by 21.7% from the current situation. Conversely, adopting a more decarbonized electricity mix (Norway) without modifying the recycled steel content results in a climate change impact reduction of 3.5%. Thus, increasing recycled steel has a greater impact-reduction potential than switching the electricity mix.

However, in the best-case scenario, climate change impacts could be reduced by 28.2% compared to the current situation. In this case, steel and chromium steel impacts would be cut by 74.7% and 9.5%, respectively.

4.2.3 | Generator type

WindTrace models different generator concepts, allowing the exploration of their environmental impacts. These concepts differ in total rare earth element mass intensity (values in brackets), with detailed element-specific breakdowns (e.g., neodymium) in Table 3 of Supporting Information S1:

1. Direct-driven permanent magnet synchronous generator (dd-pmsg) [238 t/GW]

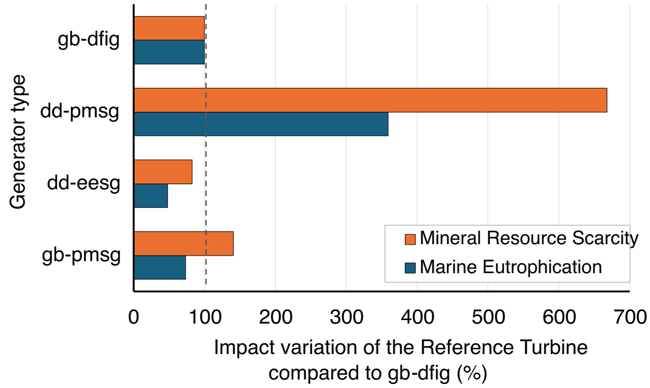

FIGURE 5 Mineral resource scarcity and marine eutrophication variation compared to the reference turbine (gb-dfig) when changing the generator type. The underlying data for this figure are provided in the "Figure 5" sheet of Supporting Information S3.

2. Gear-boxed permanent magnet synchronous generator (gb-pmsg) [61 t/GW]
3. Direct-driven electrically excited synchronous generator (dd-eesg) [45 t/GW]
4. Gear-boxed double-fed induction generator (gb-dfig) [14 t/GW]

A contribution analysis of the reference turbine equipped with gb-dfig revealed that neodymium accounted for 19.5% of marine eutrophication and 39.2% of mineral resource scarcity (Table 16 of Supporting Information S1), underscoring the importance of incorporating rare earth metals into the LCI.

Figure 5 illustrates that using the dd-pmsg generator increases impacts on mineral resource scarcity by 6.7 times and marine eutrophication by 3.6 times compared to gb-dfig. This is due to the higher intensity of neodymium and dysprosium for this generator type, which are 15 and 8.5 times greater than for gb-dfig, respectively. Consequently, the combined contribution of these two metals to the total impacts rises to 82.2% for marine eutrophication and 92.1% for mineral resource scarcity when using dd-pmsg. For gb-pmsg, neodymium and dysprosium intensities are 4.5 and 3 times higher than for gb-dfig, respectively, resulting in impact variations of 73.2% for marine eutrophication and 141% for mineral resource scarcity. Similarly, for dd-eesg, neodymium and dysprosium intensities are 2.3 and 3 times higher than for gb-dfig, respectively, leading to impact variations of 48.2% for marine eutrophication and 82.9% for mineral resource scarcity.

Although literature suggests potential impacts of rare earth metals on ionizing radiation, no significant impacts were observed in this study. These results are markedly influenced by the selected LCIA method (Section 4.1 of Supporting Information S1).

4.3 | Environmental assessment of electricity production parameters

4.3.1 | Lifetime

Figure 6 presents the climate change impacts per kWh under a varying operational lifetime ranging from 8 to 30 years, reflecting the current European mean lifetime ± 2 times the standard deviation, and considering different attrition rates. Attrition refers to the gradual wear and deterioration of wind turbines with use and depends partially on uncontrollable factors such as weather conditions and component failures, contributing to the uncertainty in a wind farm's lifetime electricity production. We included three possible attrition rates:

1. *No-attrition* ($k = 0\%$)
2. *Baseline* ($k = 0.9\%$), as in Xu et al. (2023)
3. *High attrition* ($k = 2\%$), the mean from the maximum k values in Xu et al. (2023) and Hamilton et al. (2020).

For all three options, a European average CF of 24% was applied for the first 2 years. As shown by the dashed lines in Figure 6, after 20 years, the CF remains at 24% with no attrition, drops to 20.2% under the baseline scenario, and to 16.4% with high attrition.

In the baseline, climate change impacts for an 8-year turbine lifetime (44.2 g CO_{2eq}/kWh) are 3.6 times higher than for a 30-year lifetime (12.1 g CO_{2eq}/kWh), as extending operational life effectively amortizes early life cycle impacts (e.g., materials extraction) over a larger electricity output.

Although consideration of turbine attrition has been neglected in previous LCA studies, our results show it can have a notable effect: Over an 8-year operational lifetime, high attrition reduces cumulative electricity production by only 6.7% (as the capacity factor declines from 24% to 20.8%),

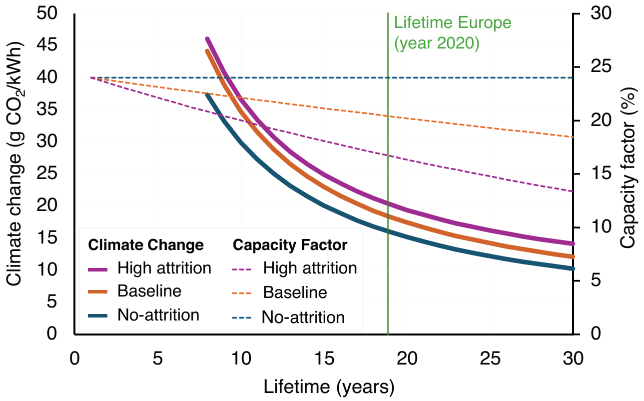

FIGURE 6 Climate change impact depending on the lifetime and attrition options (solid lines; left axis) during the lifetime of a wind turbine and evolution of the capacity factor within the lifetime of a wind turbine for different attrition rates (dashed lines; right axis). The lifetime Europe (2020) vertical green line refers to the average age of decommissioned turbines in Europe up to 2021. The underlying data for this figure are provided in the "Figure 6" sheet of Supporting Information S3.

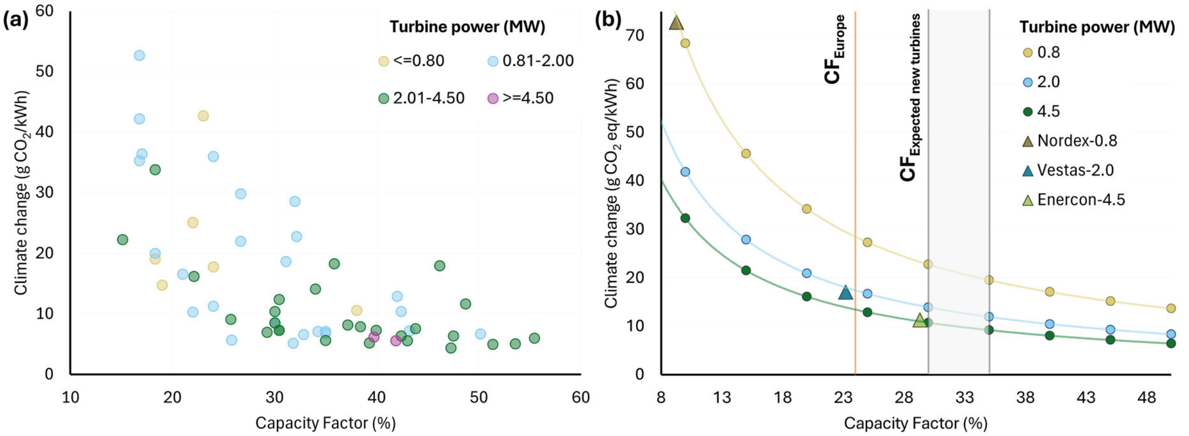

FIGURE 7 (a) Climate change impacts by capacity factor (CF) according to the literature (data details in Table 20 of Supporting Information S1); (b) climate change impact by CF of three turbine sizes using WindTrace. Equations of the curves in Table 19 of Supporting Information S1. The underlying data for this figure are provided in the "Figure 7a" and "Figure 7b" sheets of Supporting Information S3.

yet this results in a 23% increase in climate change impacts per kWh compared to the no-attrition case. For a 30-year lifetime, the increase in climate change impact per kWh reaches 38%.

Newer turbines are expected to last longer due to advancements in technology and maintenance practices (Vestas, 2024). Increasing the average European lifetime beyond the current 18.9 years to 25 years could lower impacts from 18.3 to 14.2 g CO_{2eq}/kWh, a 26% reduction under baseline attrition.

These findings are also relevant for informing repowering strategies and assessing their trade-offs (Pérez-Sánchez et al., 2025), especially as 1.6 GW of wind capacity was repowered in Europe in 2024, up from 600 MW in 2015 (WindEurope, 2025).

4.3.2 | Capacity factor

Figure 7a reviews climate change impacts per kWh across 59 studies, covering turbines from 5 kW to 6.2 MW with CF values from 15.1% to 55.4%. Reported impacts range from 4.4 to 52.7 g CO_{2eq}/kWh, averaging 14.3 g CO_{2eq}/kWh. As shown in Figure 7a, higher CF correlates with lower climate change impacts per kWh, highlighting its key role in environmental performance. However, the figure also underscores the strong influence of assumed electricity production values on the climate change results. For example, it is improbable for a turbine under 2 MW to achieve a CF as high as 50%, as one of the studies claims. This illustrates the need for greater transparency in reporting electricity production assumptions, something that is often lacking.

To understand the current and future role of capacity factors, we calculated the climate change impacts of the reference turbine (2 MW), as well as 800 kW and 4.5 MW turbines in the range of 10% to 50% CFs (baseline attrition). This demonstrates that the performance of a wind turbine can vary substantially depending on the wind conditions at the site where it is installed. To illustrate this point, we also present results for three turbines (Nordex-0.8 MW, Vestas-2.0 MW, and Enercon-4.5 MW) assessed at the same location (see Table 18 of Supporting Information S1), using site-specific CFs obtained from Renewables.ninja (Staffell & Pfenninger, 2016). Because wind speed generally increases with height, as described by the power law, taller turbines are better positioned to harness stronger and more stable winds, resulting in higher CFs than those achieved by smaller, shorter turbines. These examples underscore the critical role of local wind conditions in shaping the environmental performance of wind energy systems.

Climate change impacts show a decreasing trend with increasing CF across different turbine sizes. Impacts per kWh decrease around 80% for all turbines analyzed (Figure 7b). This pattern highlights that higher electricity production over a turbine's lifetime improves infrastructure efficiency, reducing material requirements per kWh. Thus, CF can have a greater influence on climate change than lifetime. This goes in concordance with the scalability effect discussed in Section 4.2.1 and in the literature (Figure 7a).

The current average rated power of the European turbine fleet, including early-generation installations, ranges from 660 kW to 2 MW, depending on the country (Pierrot, 2021). Assuming a CF of 24%, we estimate climate change impacts of 17.4–28.5 gCO_{2eq}/kWh. By 2023, newly installed turbines averaged 4.5 MW, while CFs were expected in the range 30%–35% (WindEurope, 2024), lowering the impacts of current turbines to 10.8–9.2 gCO_{2eq}/kWh.

4.4 | Limitations of the model

Despite its advantages, WindTrace has several limitations. Data availability for large, next-generation turbines remains scarce, introducing uncertainty in model calibration as well as in land use estimates. Our land-use intensity default values are based on farm-level data from Denholm et al. (2009), derived from turbines of 1.6 MW on average, and may not fully represent current large-scale installations. Furthermore, detailed data for certain life-cycle stages, such as turbine maintenance, were not accessible, although these can influence lifetime performance. Material demand data were sourced exclusively from Vestas, restricting comparison across alternative design configurations. Finally, the use of the cut-off approach in Ecoinvent may oversimplify recycling benefits, underscoring the need for more refined modeling of secondary material flows in future work.

5 | CONCLUDING REMARKS

WindTrace contributes to reducing the lack of open access, updated, and flexible LCI data on wind energy. It goes beyond static LCIs, helping users keep pace with the growing sizes of turbines and parks. WindTrace's key advantage over similar models lies in its integration of up-to-date, industry-sourced data from diverse datasets, its high level of detail across all life cycle phases, and its open-access availability, complemented by examples to facilitate usability. Additionally, WindTrace can support early-stage eco-design by enabling screening of environmental impacts before detailed product specifications are available.

Our results highlight important limitations in using Ecoinvent's wind turbine datasets for generalized purposes. These limitations strongly affect environmental indicators, especially climate change, marine and freshwater eutrophication, and land use, and thereby compromise the accuracy of assessments for both the existing wind fleet and future designs. This, in turn, hinders the evaluation of processes heavily dependent on renewable energy, such as those central to the European decarbonization strategy.

In contrast, WindTrace offers greater flexibility by allowing key parameters to be adjusted, acknowledging their significant influence on environmental performance. This makes it suitable to create generalized datasets for different contexts (see Supporting Information S2).

Our analysis in Section 4 highlights the complexity of wind energy environmental assessments and hints at potential improvements. The finding can be summarized as follows:

- Turbine power and hub height: the bigger the power of the turbine, the lower its climate change intensity per MW, due to economies of scale. This impact descent is exponential and shows a decrease of 38% from early 1990s turbines (700 kW; 60 m) to current (2023) turbines (4.5 MW; 100 m). We show still a 6.5% potential climate change intensity improvement if bigger turbine designs announced are implemented in the near future (7.8 MW; 120 m).
- Steel production: a potential reduction of 28.2% in the climate change impacts of wind turbines could be achieved by using a 100% recycled steel and a cleaner electricity mix (Norwegian) in the steel production.
- Generator types: The use of permanent magnet generators in direct drivetrains entails the extraction of 17 times more rare earth metals than the more conventional gear-boxed double-fed induction generator. This translates to more mineral resource scarcity and marine eutrophication impacts. However, a limitation of this study is that it does not account for the broader technical trade-offs involved in selecting one drivetrain over another.

- Lifetime: Increasing the lifetime of European wind turbines from the current 18.7 years up to 30 years would lead to a reduction of 37% kg CO_{2eq}/kWh due to infrastructure amortization. Moreover, we report for the first time the effect of mechanical wear in climate change impacts. However, a key limitation is that we do not account for the replacement of broken components or unscheduled maintenance, which could potentially offset some of the benefits of extending the lifetime.
- Capacity factor: For a given 4.5 MW turbine, increasing the CF from the current EU average of 24% to 35% (reflecting differences in site-specific wind resources) would reduce climate change impacts per kWh by 31.4%. This highlights the decisive role of location in shaping the turbine's environmental performance: The same turbine can yield very different environmental outcomes depending on the quality of the wind resource at its site.

Future WindTrace developments will also include an offshore wind module to expand its applicability to emerging offshore technologies. In parallel, refining the model to better reflect interdependencies between technical parameters represents a promising avenue for future work.

ACKNOWLEDGMENTS

This research is funded by the European Commission through project JUSTWIND4ALL (Horizon Europe GA101083936), the Spanish Research Agency (AEI) through project LIVEN (PID2020-119565RJ-I00), and the Maria de Maeztu Unit Programme for Units of Excellence of the Spanish Ministry of Science and Innovation (CEX2019-0940-M). The authors also acknowledge the Department of Research and Universities of the Generalitat de Catalunya for the financial support for the Sostenipra research group (2021 SGR 00734) and for the doctoral fellowship of A. de Tomás Pascual (2024FI-100741). J. Muñoz-Liesa would like to acknowledge the Swedish Research Council for Sustainable Development (FORMAS) funding for the ECO-FARM CITY project (Circular vertical farms to reduce environmental impacts in cities, grant number 2022–02850). The authors would like to acknowledge Dominik Huber for the insightful discussions on parametrized models of wind turbines and the existing gaps, as well as his valuable contributions in revising a preliminary version of the Supporting Information and directing us to key references on the topic.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available in the supporting information of this article. The model to produce this data is openly available in Zenodo at https://doi.org/10.5281/zenodo.14987356, and GitHub (https://github.com/LIVENlab/WindTrace_public).

ORCID

Miquel Sierra-Montoya https://orcid.org/0000-0002-7006-8911
Joan Muñoz-Liesa https://orcid.org/0000-0001-8442-6399
Laura À. Pérez-Sánchez https://orcid.org/0000-0002-6772-8456
Alexander de Tomás-Pascual https://orcid.org/0009-0002-4826-9685
Cristina Madrid-López https://orcid.org/0000-0002-4969-028X

REFERENCES

ABB. (2003). Environmental product declaration. Power transformer TrafoStar 500 MVA. https://library.e.abb.com/public/566748ad75116903c1256d630042f1af/ProductdeclarationStarTrafo500.pdf

Abeliotis, K., & Pactiti, D. (2014). Assessment of the environmental impacts of a wind farm in central greece during its life cycle. *International Journal of Renewable Energy Research*, *4*(3), 580–585. https://dergipark.org.tr/en/pub/ijrer/issue/16074/168058

Alves Dias, P., Bobba, S., Carrara, S., & Plazzotta, B., & European Commission. Joint Research Centre. (2020). *The role of rare earth elements in wind energy and electric mobility: An analysis of future supply/demand balances*. https://doi.org/10.2760/303258

Arvesen, A., & Hertwich, E. G. (2012). Assessing the life cycle environmental impacts of wind power: A review of present knowledge and research needs. *Renewable and Sustainable Energy Reviews*, *16*(8), 5994–6006. https://doi.org/10.1016/j.rser.2012.06.023

Beiter, P., Rand, J. T., Seel, J., Lantz, E., Gilman, P., & Wiser, R. (2022). Expert perspectives on the wind plant of the future. *Wind Energy*, *25*(8), 1363–1378. https://doi.org/10.1002/we.2735

Besseau, R., Sacchi, R., Blanc, I., & Pérez-López, P. (2019). Past, present and future environmental footprint of the Danish wind turbine fleet with LCA_WIND_DK, an online interactive platform. *Renewable and Sustainable Energy Reviews*, *108*, 274–288. https://doi.org/10.1016/j.rser.2019.03.030

Besseau, R., Tannous, S., Douziech, M., Jolivet, R., Prieur-Vernat, A., Clavreul, J., Payeur, M., Sauze, M., Blanc, I., & Pérez-López, P. (2023). An open-source parameterized life cycle model to assess the environmental performance of silicon-based photovoltaic systems. *Progress in Photovoltaics: Research and Applications*, *31*(9), 908–920. https://doi.org/10.1002/pip.3695

Bittner, S., Gellermann, R., & Walther, C. (2023). The radioecological footprint of electricity production by wind turbines. *Radiation Protection Dosimetry*, *199*(12), 1324–1335. https://doi.org/10.1093/rpd/ncad168

Blanc, I., Guermont, C., Gschwind, B., Menard, L., Calkoen, C., & Zelle, H. (2012). Web tool for energy policy decision-making through geo-localized LCA models: A focus on offshore wind farms in Northern Europe. In H.-K. Arndt, G. Knetsch, & W. Pillmann (Eds.), *EnviroInfo 2012 – 26th International Conference on Informatics for Environmental Protection (Part 2: Open Data and Industrial Ecological Management*, pp. 499–506). Shaker Verlag. ISBN 978-3-8440-1248-4.

BloombergNEF. (2021). *China Baowu Steel's net-zero target is just the start*. https://www.bloomberg.com/professional/insights/commodities/china-baowu-steels-net-zero-target-is-just-the-start/

Burger, B., & Bauer, C. (2007). Windkraft, in Dones, R. et al. (Eds.), Sachbilanzen von Energiesystemen: Grundlagen für den ökologischen Vergleich von Energiesystemen und den Einbezug von Energiesystemen in Ökobilanzen für die Schweiz, Final report, ecoinvent No. 6-XIII v2.0, *Paul Scherrer Institut, Villigen & Swiss Centre for Life Cycle Inventories, Dübendorf, Switzerland*. http://www.windland.ch/doku_wind/06_XIII_Windkraft.pdf

Caduff, M., Huijbregts, M. A. J., Althaus, H. J., Koehler, A., & Hellweg, S. (2012). Wind power electricity: The bigger the turbine, the greener the electricity? *Environmental Science and Technology*, *46*(9), 4725–4733. https://doi.org/10.1021/es204108n

Caduff, M., Huijbregts, M. A. J., Koehler, A., Althaus, H.-J. J., & Hellweg, S. (2014). Scaling relationships in life cycle assessment: The case of heat production from biomass and heat pumps. *Journal of Industrial Ecology*, *18*(3), 393–406. https://doi.org/10.1111/jiec.12122

Carrara, S., Alves Dias, P., Plazzotta, B., & Pavel, C. (2020). *Raw materials demand for wind and solar PV technologies in the transition towards a decarbonised energy system, EUR 30095 EN*. Publications Office of the European Union. https://doi.org/10.2760/160859

Denholm, P., Hand, M., Jackson, M., & Ong, S. (2009). *Land-use requirements of modern wind power plants in the United States: Vol. Technical (Issue August)*. National Renewable Energy Laboratory.

Depraiter, L., & Goutte, S. (2023). The role and challenges of rare earths in the energy transition. *Resources Policy*, *86*, 104137. https://doi.org/10.1016/j.resourpol.2023.104137

Elsam Engineering. (2004). *Life Cycle Assessment of offshore and onshore sited wind farms*. https://www.osti.gov/etdeweb/servlets/purl/20903080

Eurofer. (2022). *European Steel in Figures 2022*. https://www.eurofer.eu/publications/brochures-booklets-and-factsheets/european-steel-in-figures-2022

Eurofer. (2024). *European Steel in Figures 2024*. https://www.eurofer.eu/publications/brochures-booklets-and-factsheets/european-steel-in-figures-2024

European Commission. (2020). *A hydrogen strategy for a climate-neutral Europe*. COM2020/301. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A52020DC0301

European Commission. (2023). *European Wind Power Action Plan*. COM/2023/669. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A52023DC0669&qid=1702455143415

Germer, S., & Kleidon, A. (2019). Have wind turbines in Germany generated electricity as would be expected from the prevailing wind conditions in 2000–2014? *PLoS ONE*, *14*(2), e0211028. https://doi.org/10.1371/journal.pone.0211028

Gschneidner, K. A., & Pecharsky, V. K. (2024). *Rare-earth element. Processing ores*. Encyclopedia Britannica. https://www.britannica.com/science/rare-earth-element/Processing-ores

Guinée, J. B., Heijungs, R., Huppes, G., Zamagni, A., Masoni, P., Buonamici, R., Ekvall, T., & Rydberg, T. (2011). Life cycle assessment: Past, present, and future. *Environmental Science & Technology*, *45*(1), 90–96. https://doi.org/10.1021/es101316v

Hamilton, S. D., Millstein, D., Bolinger, M., Wiser, R., & Jeong, S. (2020). How does wind project performance change with age in the United States? *Joule*, *4*(5), 1004–1020. https://doi.org/10.1016/j.joule.2020.04.005

Hellweg, S., & Milà Canals, L. (2014). Emerging approaches, challenges and opportunities in life cycle assessment. *Science*, *344*(6188), 1109–1113. https://doi.org/10.1126/science.124836

Holappa, L. (2020). A general vision for reduction of energy consumption and CO_2 emissions from the steel industry. *Metals*, *10*(9), 1–20. https://doi.org/10.3390/met10091117

Huijbregts, M. A. J., Steinmann, Z. J. N., Elshout, P. M. F., Stam, G., Verones, F., Vieira, M., Zijp, M., Hollander, A., & van Zelm, R. (2017). ReCiPe2016: A harmonised life cycle impact assessment method at midpoint and endpoint level. *International Journal of Life Cycle Assessment*, *22*(2), 138–147. https://doi.org/10.1007/s11367-016-1246-y

Institure for Energy Economics and Financial Analysis. (2022). *The facts about steelmaking. Steelmakers seeking Green steel*. https://ieefa.org/resources/facts-about-steelmaking-steelmakers-seeking-green-steel

International Energy Agency. (2020). *Iron and Steel Technology Roadmap Towards more sustainable steelmaking*. https://www.iea.org/reports/iron-and-steel-technology-roadmap

International Organization for Standardization. (2020). *ISO 14006:2020 – Environmental management systems: Guidelines for incorporating ecodesign*. https://www.iso.org/standard/72644.html

Jolivet, R., Clavreul, J., Brière, R., Besseau, R., Prieur Vernat, A., Sauze, M., Blanc, I., Douziech, M., & Pérez-López, P. (2021). lca_algebraic: A library bringing symbolic calculus to LCA for comprehensive sensitivity analysis. *International Journal of Life Cycle Assessment*, *26*(12), 2457–2471. https://doi.org/10.1007/s11367-021-01993-z

Jung, C., & Schindler, D. (2023). Reasons for the recent onshore wind capacity factor increase. *Energies*, *16*(14), 5390. https://doi.org/10.3390/en16145390

Kupfer, T., Baitz, M., Colodel, C. M., Kokborg, M., Schöll, S., Rudolf, M., Bos, U., Bosch, F., Gonzalez, M., Schuller, O., Hengstler, J., Stoffregen, A., Thylmann, D., & Koffler, C. (2021). *GaBi databases & modelling principles*. Sphera.

Li, C., Mogollón, J. M., Tukker, A., Dong, J., von Terzi, D., Zhang, C., & Steubing, B. (2022). Future material requirements for global sustainable offshore wind energy development. *Renewable and Sustainable Energy Reviews*, *164*, 112603. https://doi.org/10.1016/j.rser.2022.112603

Li, C., Mogollón, J. M., Tukker, A., & Steubing, B. (2022). Environmental impacts of global offshore wind energy development until 2040. *Environmental Science and Technology*, *56*(16), 11567–11577. https://doi.org/10.1021/acs.est.2c02183

Li, J., Peng, K., Wang, P., Zhang, N., Feng, K., Guan, D., Meng, J., Wei, W., & Yang, Q. (2020). Critical rare-earth elements mismatch global wind-power ambitions. *One Earth*, *3*(1), 116–125. https://doi.org/10.1016/j.oneear.2020.06.009

Mello, G., Ferreira Dias, M., & Robaina, M. (2020). Wind farms life cycle assessment review: CO_2 emissions and climate change. *Energy Reports*, *6*, 214–219. https://doi.org/10.1016/j.egyr.2020.11.104

Mendecka, B., & Lombardi, L. (2019). Life cycle environmental impacts of wind energy technologies: A review of simplified models and harmonization of the results. *Renewable and Sustainable Energy Reviews*, *111*, 462–480. https://doi.org/10.1016/j.rser.2019.05.019

Mutel, C. (2017). Brightway: An open source framework for Life Cycle Assessment. *The Journal of Open Source Software*, *2*(12), 236. https://doi.org/10.21105/joss.00236

Olauson, J., Edström, P., & Rydén, J. (2017). Wind turbine performance decline in Sweden. *Wind Energy*, *20*(12), 2049–2053. https://doi.org/10.1002/we.2132

Padey, P., Girard, R., Le Boulch, D., & Blanc, I. (2013). From LCAs to simplified models: A generic methodology applied to wind power electricity. *Environmental Science and Technology*, *47*(3), 1231–1238. https://doi.org/10.1021/es303435e

Pérez-Sánchez, L. À., Sierra-Montoya, M., & Madrid-López, C. (2025). Trade-offs of electricity production, and life cycle impacts in scenarios of repowering and life extension of an onshore wind park in Portugal. *Manuscript in preparation*.

Pierrot, M. (2021). *World wind farms database*. https://www.thewindpower.net/

Pizzol, M., Sacchi, R., Köhler, S., & Anderson Erjavec, A. (2021). Non-linearity in the life cycle assessment of scalable and emerging technologies. *Frontiers in Sustainability*, *1*, 611593. https://doi.org/10.3389/frsus.2020.611593

Price, L., & Kendall, A. (2012). Wind power as a case study: Improving life cycle assessment reporting to better enable meta-analyses. *Journal of Industrial Ecology*, *16*(S1), S22–S27. https://doi.org/10.1111/j.1530-9290.2011.00458.x

Sacchi, R. (2021). *Windisch [GitHub repository]*. https://github.com/romainsacchi/windisch

Sacchi, R., Besseau, R., Pérez-López, P., & Blanc, I. (2019). Exploring technologically, temporally and geographically-sensitive life cycle inventories for wind turbines: A parameterized model for Denmark. *Renewable Energy*, *132*, 1238–1250. https://doi.org/10.1016/j.renene.2018.09.020

Sacchi, R., Terlouw, T., Siala, K., Dirnaichner, A., Bauer, C., Cox, B., Mutel, C., Daioglou, V., & Luderer, G. (2022). PRospective EnvironMental Impact asSEment (premise): A streamlined approach to producing databases for prospective life cycle assessment using integrated assessment models. *Renewable and Sustainable Energy Reviews*, *160*, 112311. https://doi.org/10.1016/j.rser.2022.112311

Shu, W., Zhang, Q., Audet, J., Li, Z., Leng, P., Qiao, Y., Tian, C., Chen, G., Zhao, J., Cheng, H., & Li, F. (2024). Non-negligible N_2O emission hotspots: Rivers impacted by ion-adsorption rare earth mining. *Water Research*, *251*, 121124. https://doi.org/10.1016/j.watres.2024.121124

Sieros, G., Chaviaropoulos, P., Sørensen, J. D., Bulder, B. H., & Jamieson, P. (2012). Upscaling wind turbines: Theoretical and practical aspects and their impact on the cost of energy. *Wind Energy*, *15*(1), 3–17. https://doi.org/10.1002/we.527

Sierra-Montoya, M. (2024). *WindTrace software*. https://doi.org/10.5281/zenodo.14987356

Sonderegger, T., & Stoikou, N. (2022). *Implementation of life cycle impact assessment methods in the ecoinvent database v3.9 and v3.9.1* (Version 1.1, 2023-01-23). Ecoinvent Association. https://support.ecoinvent.org/hubfs/LCIA_implementation_3.9-and-3.9.1.pdf?hsLang=en

Staffell, I., & Green, R. (2014). How does wind farm performance decline with age? *Renewable Energy*, *66*, 775–786. https://doi.org/10.1016/j.renene.2013.10.041

Staffell, I., & Pfenninger, S. (2016). Using bias-corrected reanalysis to simulate current and future wind power output. *Energy*, *114*, 1224–1239. https://doi.org/10.1016/j.energy.2016.08.068

Stehly, T., Duffy, P., & Mulas Hernando, D. (2024). *Cost of wind energy review: 2024*. https://www.energy.gov/eere/wind/wind-market-reports-2024-edition

Telsnig, T., Georgakaki, A., Letout, S., Kuokkanen, A., Mountraki, A., Ince, E., Shtjefni, D., Joanny Ordonez, G., Eulaerts, O., & Grabowska, M. (2022). *Clean Energy Technology Observatory: Wind energy in the European Union –2022 Status report on technology development, trends, value chains and markets*. https://doi.org/10.2760/855840

Tvindkraft. (n.d.). *What is Tvindkraft?* Retrieved September 16, 2024 from https://www.tvindkraft.dk/what-is-tvindkraft-a-pioneer-of-wind-energy/

Verma, S., Paul, A. R., & Haque, N. (2022). Assessment of materials and rare earth metals demand for sustainable wind energy growth in India. *Minerals*, *12*(5), 647. https://doi.org/10.3390/min12050647

Vestas. (2015). *Life cycle assessment of electricity production from an onshore V112-3.3 MW wind plant* – 21st September 2015, Version 2.1. Vestas Wind Systems A/S, Hedeager 42, Aarhus N, 8200, Denmark. https://www.vestas.com/content/dam/vestas-com/global/en/sustainability/reports-and-ratings/lcas/Life%20cycle%20assessment_V112-3%203MW_Mk2c_Version_2_1_210915.pdf.coredownload.inline.pdf

Vestas. (2022). *Life cycle assessment of electricity production from an onshore V162-6.2 MW wind plant* – 31st January 2023. Vestas Wind Systems A/S, Hedeager 42, Aarhus N, 8200, Denmark. https://www.vestas.com/content/dam/vestas-com/global/en/sustainability/reports-and-ratings/lcas/LCA%20of%20Electricity%20Production%20from%20an%20onshore%20EnVentus%20V162-6.2.pdf.coredownload.inline.pdf

Vestas. (2024). *Life cycle assessment of electricity production from an offshore V236-15 MW wind plant– 17th April 2024. Vestas Wind Systems A/S, Hedeager 42, Aarhus N, 8200, Denmark*. https://www.vestas.com/content/dam/vestas-com/global/en/sustainability/environment/LCA%20of%20Electricity%20Production%20from%20an%20offshore%20V236-15MW.pdf.coredownload.inline.pdf

Weinzettel, J., & Kovanda, J. (2009). Assessing socioeconomic metabolism through hybrid life cycle assessment: The case of the Czech Republic. *Journal of Industrial Ecology*, *13*(4), 607–621. https://doi.org/10.1111/j.1530-9290.2009.00144.x

Wernet, G., Bauer, C., Steubing, B., Reinhard, J., Moreno-Ruiz, E., & Weidema, B. (2016). The ecoinvent database version 3 (part I): Overview and methodology. *International Journal of Life Cycle Assessment*, *21*(9), 1218–1230. https://doi.org/10.1007/s11367-016-1087-8

WindEurope. (2019). *Wind energy in Europe in 2018: Trends and statistics*. https://windeurope.org/data/products/wind-energy-in-europe-in-2018-trends-and-statistics/

WindEurope. (2024). *Wind energy in Europe - 2023 Statistics and the outlook for 2024–2030*. https://windeurope.org/data/products/wind-energy-in-europe-2023-statistics-and-the-outlook-for-2024-2030/

WindEurope. (2025). *Wind energy in Europe: 2024 Statistics and the outlook for 2025–2030*.

Xu, J., Zou, J., Ziegler, A. D., Wu, J., & Zeng, Z. (2023). What drives the change of capacity factor of wind turbine in the United States? *Environmental Research Letters*, *18*(6), 064009. https://doi.org/10.1088/1748-9326/acce4f

Zimmermann, T. (2013). Parameterized tool for site specific LCAs of wind energy converters. *International Journal of Life Cycle Assessment*, *18*(1), 49–60. https://doi.org/10.1007/s11367-012-0467-y

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Sierra-Montoya, M., Muñoz-Liesa, J., Pérez-Sánchez, L. À., de Tomás-Pascual, A., & Madrid-López, C. (2025). WindTrace: Assessing the environmental impacts of wind energy designs with a parametric life cycle inventory model. *Journal of Industrial Ecology*, 1–15. https://doi.org/10.1111/jiec.70114