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Cost-Potential Curves of Onshore Wind Energy: the Role of Disamenity Costs

Oliver Ruhnau¹ · Anselm Eicke¹ · Raffaele Sgarlato¹ · Tim Tröndle² · Lion Hirth¹

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Abstract

Numerical optimization models are used to develop scenarios of the future energy system. Usually, they optimize the energy mix subject to engineering costs such as equipment and fuel. For onshore wind energy, some of these models use cost-potential curves that indicate how much electricity can be generated at what cost. These curves are upward sloping mainly because windy sites are occupied first and further expanding wind energy means deploying less favorable resources. Meanwhile, real-world wind energy expansion is curbed by local resistance, regulatory constraints, and legal challenges. This presumably reflects the perceived adverse effect that onshore wind energy has on the local human population, as well as other negative external effects. These disamenity costs are at the core of this paper. We provide a comprehensive and consistent set of cost-potential curves of wind energy for all European countries that include disamenity costs, and which can be used in energy system modeling. We combine existing valuation of disamenity costs from the literature that describe the costs as a function of the distance between turbine and households with gridded population data, granular geospatial data of wind speeds, and additional land-use constraints to calculate such curves. We find that disamenity costs are not a game changer: for most countries and assumptions, the marginal levelized cost of onshore wind energy increase by 0.2–12.5 €/MWh.

Keywords Cost-potential curves · Energy system modeling · Disamenity costs · Onshore wind energy · Setback distances

1 Introduction

Numerical cost optimization models of the energy system are used to develop scenarios of the future electricity generation mix. Under the constraint of net-zero greenhouse gas emissions by mid-century, the results of these cost optimization models often entail a very substantial expansion of onshore wind energy. This expansion often is reported to come

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at relatively low cost, being concentrated in areas with high wind speeds. Meanwhile, the real-world expansion of onshore wind energy falls short in comparison to the modeled scenarios. In many places it has even slowed down compared to historical observations. The sluggishness of wind power expansion is often attributed to local resistance, presumably due to an adverse impact of turbines on natural amenities, their visual and noise impact, flicker, or a loss in scenery (e.g., Krekel and Zerrahn 2017; McKenna et al. 2021). These effects can be described as “disamenity costs”, that is, the monetarization of the perceived adverse effect onshore wind energy has on the local human population. These are one type of negative implications of wind turbines, along with the impact on wildlife.

Most existing energy system models today do not account for disamenity costs. Instead, they minimize engineering cost subject to technical as well as environmental land eligibility constraints. The simplest approach for modeling onshore wind energy expansion is a single assumption on the levelized cost of electricity (LCOE) per geography, which may be derived from investment cost and typical capacity factors. Models are then allowed to build wind power until the technical potential is reached (e.g., Bogdanov et al. 2019; Ruhnau et al. 2022). Other models use a more detailed approach using long-term supply (or cost-potential) curves (e.g., Tröndle et al. 2020; Neumann 2021). Cost-potential curves indicate how much electricity can be generated at what cost: they show annual generation or installed capacity on the x-axis and levelized cost on the y-axis. These curves are upward sloping because windy sites are occupied first, and less favorable resources need to be deployed subsequently.¹

In addition to technical and environmental constraints, some energy system models consider social acceptance when determining land eligibility. One common approach is to define a minimum distance between wind turbines and settlements to avoid adverse effects on local population. Many studies have estimated the feasible potential, with a wide range of results, depending on the underlying assumptions (e.g., Grassi et al. 2012; McKenna et al. 2014; Sánchez-Lozano et al. 2014; Watson and Hudson, 2015; Samsatli et al. 2016; Baseer et al. 2017; Ryberg et al. 2018). For example, Watson and Hudson (2015) and Samsatli et al. (2016) obtain very different results for land availability for onshore wind energy in southern England. The former study finds that 37.8% of the area is eligible for wind turbines while the latter merely classifies 2% of the land as usable. This indicates the difficulties and arbitrariness of defining such constraints.

In practice, hardly any of the exclusion criteria is (or must be) a hard constraint. Instead of a binary classification, reality is more nuanced. Obstacles such as areas being protected for environmental reasons or proximity to human settlements make wind investments less likely, but, in general, not outright impossible. For example, Harper et al. (2019) study the likelihood that certain technological, legislative, and social constraints prevent the construction of wind turbines in the UK. Similarly, McKenna et al. (2021) analyze the tradeoff between building wind turbines in wind-rich regions and beautiful landscapes. The authors find evidence that planning applications for onshore wind are more likely to be rejected in more scenic areas. Eichhorn et al. (2019) present a framework for assessing possible wind sites based on environmental, social, technical, and economic aspects. Applying the framework to Germany, the authors find strong trade-offs between the different objectives. These studies name the trade-offs and compare solutions qualitatively.

¹ The fact that technological learning may drive down costs over time is typically included in separate equations.

There is a small branch of the literature that studies the impact of internalizing disamenity costs in expansion and siting decisions. Lohr et al. (2022) assess the effect of internalizing environmental costs in a strongly simplified model. They observe a strong shift in technology mix and the placement of generators. Lehmann et al. (2021) analyze how taking local disamenities into account changes the optimal siting of turbines in Germany. They find a significant spatial trade-off between the engineering cost and the disamenity costs: considering disamenity costs substantially alters the optimal siting patterns. Grimsrud et al. (2021) study the effect of internalizing the external costs of wind turbines, finding that accounting for such costs lowers the social cost of new wind turbines significantly. Tafarte and Lehmann (2021) investigate trade-offs between the most relevant criteria for siting wind turbines: engineering costs, disamenities for local residents, the aesthetic quality of the landscape, local nature conservation, and biodiversity impacts. The authors find that the cumulated costs vary significantly between when optimizing according to these criteria.

The main objective of this work is to provide a set of onshore wind energy cost-potential curves for European countries to be used as inputs in energy system and power market modeling in the context of net-zero emission scenarios. This research is hence best understood as a service to the energy modeling community. To this end we use existing valuation of disamenity costs of wind turbines from the literature that describe the costs as a function of the distance between turbine and households, which we combine with gridded population data. This is essentially done in four steps: (a) creating a European dataset of “nearby population” for European geolocations drawing on population data from Eurostat, (b) using existing valuation of disamenity costs from the academic literature on choice experiments to calculate a map of disamenity costs of onshore wind energy, (c) calculating a map of engineering cost based on reanalysis wind speed data using *renewables.ninja* (Staffell and Pfenninger 2016), and (d) determining turbine locations given land eligibility constraints using the geospatial tool GLAES (Ryberg et al. 2018). Combining these turbine locations with the engineering and disamenity cost maps yields cost-potential curves that include disamenity costs. Code and data will be available on Zenodo and GitHub, respectively, under a CC-BY license that allows wide re-use (see Code & Data Availability statement at the end of this article).

Despite the limitations of summarizing granular data in high-level statements, we think it is fair to say that our results show that disamenity costs are, by and large, not a game changer. Even when considering a truly massive expansion of wind energy and using upper end cost estimates we find that the disamenity costs increase the marginal LCOE of onshore wind energy by not more than 15 €/MWh in most Europe countries, and much less in some. However, in some of the most densely populated countries such as the Benelux region, the impact of disamenity costs can reach toward 25 €/MWh. Lower end disamenity cost estimates yield an impact on the marginal LCOE in the order of magnitude of 1 €/MWh. Compared to the gap in engineering costs between onshore wind and nuclear energy, to the decline in wind energy engineering cost in the past decade, or to the social cost of carbon of fossil-fuel electricity, these numbers are quite small.

The remainder of this paper is structured as follows: Sect. 2 describes the methods used to derive the cost-potential curves, Sect. 3 presents some analysis of the cost-potential curves with a focus on the impact of disamenity costs, Sect. 4 discusses the limitations of the methods and the implications of the results, and Sect. 5 draws conclusions.

2 Methods

This section describes our literature-based assumptions on disamenity cost curves (Sect. 2.1), how these are combined with population data to derive disamenity cost maps (Sect. 2.2), our method for calculating engineering costs based on resource potentials (Sect. 2.3), and the framework we use to determine the optimal turbine placement and the resulting cost-potential curves (Sect. 2.4).

2.1 Disamenity Cost Functions

There is no market for wind-turbine related disamenities. Hence, disamenity costs cannot be observed but need to be estimated. The existing literature uses three different approaches for such estimates: hedonic prices, choice experiments, and the life satisfaction approach. We discuss these approaches in the following.

The method of hedonic pricing is used to estimate disamenity costs based on observed housing prices. It can hence be classified as a “revealed preferences” approach. The underlying idea is that disamenities from wind energy may lower the prices for nearby property, in particular houses. This could be because owners obtain a lower utility from living in the affected houses themselves or a lower rent from tenants with a reduced willingness to pay. Existing studies that estimate the disamenity costs of wind energy based on housing prices yield ambiguous results. While many US studies find no significant effects (Lang et al. 2014; Hoen et al. 2015; Hoen and Atkinson-Palombo 2016), several European studies find a significant reduction in prices of nearby houses of -1.4% to -14% (Jensen et al. 2014; Gibbons 2015; Dröes and Koster 2016; Sunak and Madlener 2016; Frondel et al. 2019). Because property value data for all potentially affected houses across Europe is unavailable, we reject hedonic pricing for evaluating disamenity costs of wind turbines within the European scope of this paper.

In contrast to hedonic prices, choice experiments fall within the category of “stated preferences” approaches. As part of the experiment, probands are asked to compare several wind farms, which differ by properties such as proximity, height, and the number of turbines, and state their willingness to pay (WTP) for realizing the wind farm they prefer or a willingness to accept (WTA) the outcome they dislike. Wen et al. (2018) provide a review and quantitative synthesis of such choice experiments. Across the reviewed studies, the most significant and consistent result is that the disamenity costs decrease with the distance between wind turbines and the probands’ homes. The effect of a change in the number of turbines and in the turbine height are ambiguous. We hence focus on the relationship between disamenity and proximity. Most studies quantify the WTP as a function of the distance to a wind turbine. As an average of the reviewed studies, Wen et al. (2018) derive a formula for the WTP as a function of the distance d that, when converted to €/person/turbine/year,² yields:

$$WTP = -3.6 \cdot \ln(d) + k \quad (1)$$

By design, choice experiments estimate the relative value of a change in distance, but not the disamenity costs of a wind turbine in absolute terms. Hence, this approach cannot

² Wen et al. provide estimates in GBP/household/farm/year. We assume an exchange rate of 0.86 GBP/EUR, 2 persons per household, and 5 turbines per wind farm.

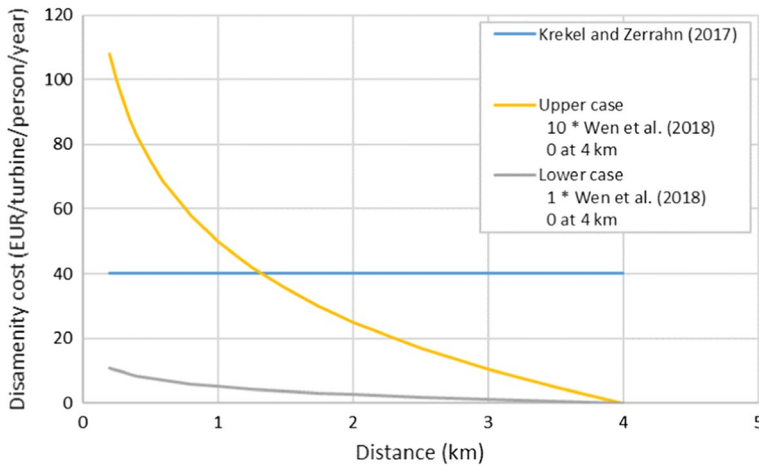


Fig. 1 Disamenity cost functions

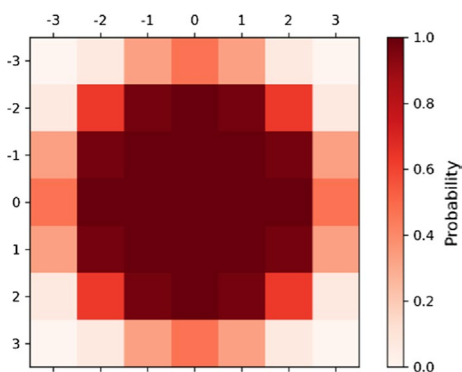
provide information on the constant k in the above formula. It is important to note that estimates for the WTP are usually significantly lower than for the WTA due to income effects, that is, respondents' WTP is lower because of their limited financial capacities. In a general review, Horowitz and McConnell (2002) report an average WTA/WTP-ratio of about 7 for all goods and about 10 for non-market good, the category to which wind energy disamenity would belong. Even though we are not aware of a systematic WTA/WTP comparison for wind energy, it seems likely that the WTP estimation underestimates the actual disamenity costs.

The third approach is the life satisfaction approach. As an alternative to evaluating stated and revealed preferences, it estimates the impact of nearby wind turbines on self-reported life satisfaction, while controlling for income and other relevant confounders. The disamenity costs are derived by determining the increase in income needed to compensate the reduction in life satisfaction due to nearby wind turbines. Krekel and Zerrahn (2017) use this approach to estimate the disamenity costs of wind energy in Germany. They find average disamenity costs of about 40 €/person/turbine/year³ for households within 4 km distance from the wind turbine, and no significant result for distances above 4 km. As the authors state, a significant limitation of this approach is that "quantifications using well-being data may overestimate the monetary effect of an environmental externality" (Krekel and Zerrahn, 2017). One reason for this is that likely measurement errors in the income variable may bias downward the estimated effect of life satisfaction on income. This would lead to an overestimation of the income needed to compensate the wind-related satisfaction loss (Frey et al. 2004).

Based on this literature, we define an upper and a lower case for the disamenity costs $c(d)$ as follows and as displayed in Fig. 1:

³ Krekel and Zerrahn report 150–250 €/person/farm/year. For conversion, we assume 5 turbines/farm.

Fig. 2 Probability matrix for a distance of 3 km. The values represent the probability of a randomly placed inhabitant in the corresponding cells being within 3 km of a randomly placed turbine placement at center cell



$$c(d) = \begin{cases} -3.6 \cdot \ln(d) + 5.0 & \text{lowercase} \\ -36.0 \cdot \ln(d) + 50.0 & \text{uppercase} \end{cases} \quad (2)$$

For the lower case, we use the WTP function from Wen et al. (2018) Eq. (1) and parametrize the constant k such that wind disamenities become zero at 4 km, reflecting the finding of Krekel and Zerrahn (2017). This lower-case function is about one order of magnitude smaller than the estimate from Krekel and Zerrahn, which is not surprising given that WTP estimates tend to be low compared to WTA values and given that the life satisfaction approach tends to overestimate disamenity costs. For the lower case, we multiply the lower-case function by a factor of ten, which yields a function that is in the order of magnitude of Krekel and Zerrahn and which is in line with the general intuition from Horowitz and McConnell (2002) that estimates for the WTA could be 10 times larger than for the WTP in the case of non-market goods. The magnitude of the difference between our lower and higher cases reflects that the uncertainty regarding the disamenity costs of wind energy is high—a limitation which should be kept in mind when interpreting our (or any other) analysis on the implications of disamenity costs.

Note that the literature and, therefore, our analysis assumes a *homo oeconomicus* in the sense that the disamenity costs depend only on nearby turbines and not on how the remaining population is affected. By contrast, people may behave more like a *homo reciprocans* in the sense that they feel a negative utility if other people are exposed to less turbines than themselves. This could be an argument in favor of a more equitable distribution of wind turbines although such a distribution would not be cost-optimal in the sense of our analysis.

2.2 Disamenity Cost Maps

Our calculation of disamenity cost maps is based on the GEOSTAT population dataset,⁴ which reports the number of inhabitants in a 1×1 km grid. For each cell in this grid, we estimate the number of inhabitants within a given distance $p_j(d)$ of a wind turbine located in the cell j . Because of the 1×1 km resolution, there is some ambiguity about the distribution of the population within each raster cell. Likewise, there is uncertainty about the

⁴ <https://ec.europa.eu/eurostat/web/gisco/geodata/reference-data/population-distribution-demography/geostat>.

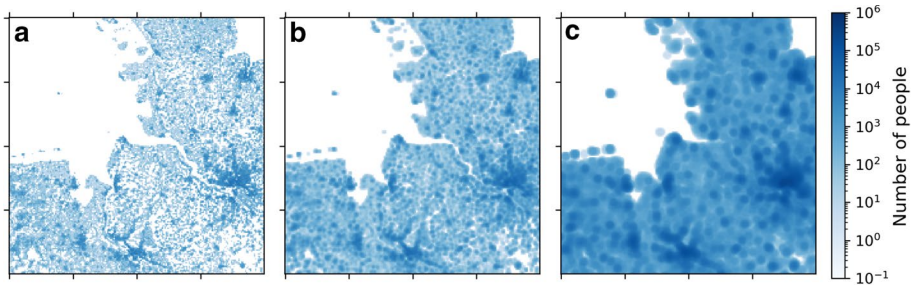


Fig. 3 Original population dataset (inhabitants per km²) **a**, population within a distance of 1 km **b**, and population within a distance of 3 km **c** for the example of north-western Germany

exact position of a wind turbine within a raster cell. Here, we use a stochastic approach that calculates the probability that the distance between a randomly placed turbine in one cell and a randomly placed inhabitant in another cell is below a certain threshold. This approach is conservative as it neglects the potential of optimizing turbine placement within a cell. In reality, population will often be concentrated in specific locations within a cell, and an optimized turbine placement could avoid these locations within a cell. This would lead to larger distances between turbines and population and, therefore, lower disamenity costs compared to our approach. Figure 2 illustrates the resulting probability matrix $m_{a,b}(d)$ for the distance $d = 3$ km.

Counting the population within a certain distance $p_j(d)$ is efficiently achieved by convoluting the probability matrix $m_{a,b}(d)$ with the original population dataset p_j :

$$p_j(d) = \sum_{a=-d}^{+d} \sum_{b=-d}^{+d} m_{a,b}(d) \cdot p_{j_{a,b}}, \quad (3)$$

where $j_{a,b}$ is the cell resulting from offsetting j by a and b , with $j_{0,0} \stackrel{\text{def}}{=} j$. Figure 3 displays an extract of the original population dataset (a) alongside the resulting datasets for the population within the distance of 1 km (b) and 3 km (c).

The derived population counts $p_j(d)$ are combined with the disamenity cost function $c(d)$ from Sect. 2.1 to calculate disamenity costs C_j for a turbine located in the cell j as follows:

$$C_j = \sum_{i=1}^4 (p_j(d_i) - p_j(d_{i-1})) \cdot \int_{d_{i-1}}^{d_i} c(r) \cdot 2\pi r dr, \quad (4)$$

$$d_0 = 0.2 \text{ km, and } d_i = i \text{ km } \forall i \in \mathbb{Z}^+,$$

where $d_i - d_{i-1}$ are distance intervals. The first part of the equation calculates the number of inhabitants within this distance interval, and the second part calculates the average disamenity cost for an inhabitant within this distance interval, assuming a uniform geographic distribution. Note that the disamenity cost function is not defined for zero and that we set the minimum distance d_0 to 0.2 km, which is in line with the minimum distance from

Fig. 4 Disamenity cost map (for the low disamenity cost scenario)

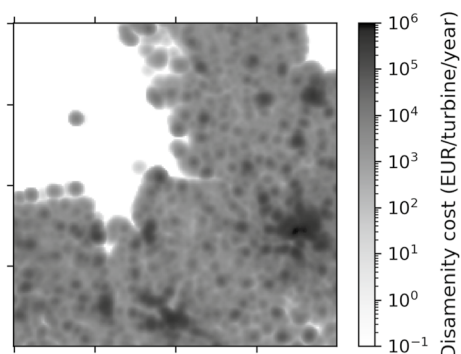


Table 1 Financial assumptions for calculating the levelized cost of electricity

Parameter	Value	Unit	Source
Investment cost	1040	€/kW	Danish Energy Agency (2022)
Fixed O&M cost	16.8	€/kW/yr	Danish Energy Agency (2022)
Lifetime	30	yrs	Danish Energy Agency (2022)
WACC	5	%	Own assumption
Availability	90	%	European Environment Agency (2009)

O&M operation and maintenance; WACC weighted average cost of capital

settlements as implemented in the turbine placement algorithm (see Sect. 2.4) Fig. 4) illustrates and extract of the resulting disamenity cost map (same area as displayed in Fig. 3).

2.3 Engineering Cost Maps

To derive a European map of engineering cost of wind power, we first simulate electricity yields in all locations, and we then derive the levelized cost of electricity using a range of financial parameters.

We calculate electricity yields using simulated capacity factor time series from Tröndle et al. (2019).⁵ The time series are simulated using *renewables.ninja* (Staffell and Pfenniger 2016) from MERRA-2 weather data for ~2700 onshore locations in Europe. At all locations, the same wind turbine is assumed: Vestas V90 2000 (the most-built wind turbine between 2010 and 2018 in Europe), with a hub height of 105 m (median hub height in the same period). The time series comprise 17 years, from 2000 to 2016, and we use the mean to derive annual electricity yields.

We derive the levelized cost of electricity from electricity using financial parameters given in Table 1. The parameters are projections for the year 2030 and, therefore, slightly below today's values.

⁵ The dataset is available via <https://doi.org/10.5281/zenodo.3533038>.

Table 2 Exclusion criteria and excluded areas for the placement of wind turbines, based on Ryberg et al. (2018)

Exclusion criteria	Threshold
Altitude above sea level	1800 m
Maximum slope (degrees)	10°
Excluded areas	With minimum distance
Lakes	400 m
Rivers	200 m
Settlement areas	200 m
Industrial, commercial, and mining areas	300 m
Roads (primary & secondary)	200 m
Railways	150 m
Airports	5000 m
Power lines (> 110 kV)	200 m
National parks	1000 m
Natura 2000 (protected habitats and protected birds)	1500 m
Protected reserves	500 m
Biospheres	300 m
Landscape protection areas	500 m
Natural monuments	1000 m
Protected wilderness	1000 m

2.4 Turbine Placement

To construct cost-potential curves, we first determine the placement of turbines given land eligibility constraints using the Geospatial Land Availability for Energy Systems (GLAES) package by Ryberg et al. (2018). The considered land eligibility constraints are summarized in Table 2.⁶ They are, with the exception of the distance to settlements, taken from a literature review by Ryberg et al. (2018) covering 43 studies from countries worldwide. The actual constraints vary substantially between and even within countries, and there are many exceptions to the assumed constraints (Hedenus et al. 2022). In addition, changes in the corresponding laws may hinder or ease the permission of wind turbines in certain areas. Hence, the implemented constraints should be interpreted as an approximation of the very heterogeneous real-world conditions. A more precise representation of this heterogeneity would require an extensive and detailed policy review that goes beyond the scope of this study.

For our main scenario, we deliberately choose a relatively small minimum distance from settlement areas (200 m) to explore the disamenity costs related to potential turbine placement near settlements. In a sensitivity analysis, we increase the minimum distance from settlement areas to contrast the costs of such a hard restriction and contrast the arising costs with the disamenity costs resulting from the placement closer to settlements.

Given the eligible land resulting from the above exclusion criteria, the GLAES algorithm determines the turbine placement that maximizes the number of turbines in a

⁶ Altitude and slope are taken from the Digital Elevation Model over Europe (EU-DEM), which has a spatial resolution of 30 m (Ryberg et al. 2018).

predetermined region. Note that turbines are placed on a much higher resolution than the 1 km² of the cost maps. The distance between any two turbines is at least 500 m. The number of turbines multiplied by a turbine capacity of 2 MW per turbine yields the techno-ecological potential (given the social constraints defined in Table 2).⁷

The resulting placement renders a more conservative potential for onshore wind energy compared to previous studies. For example, the techno-ecological potential that we estimate for Germany is slightly below 600 GW, while previous studies with less conservative assumptions on buffer zones yield potentials between 1200 GW (UBA, 2013) and 1500 GW (Bofinger et al. 2011).

The techno-ecological potential is much larger than what can be expected to be built. Therefore, we refer to political expansion targets to identify a realistic range of onshore wind capacity expansion. Unfortunately, there is no official European net-zero energy scenario. On the one hand, the latest scenario extending to 2050 is the EU reference scenario from 2020,⁸ which does not meet the net-zero emission target defined in the EU Green Deal. On the other hand, the more recent and more ambitious EU Green Deal scenarios⁹ are on a net-zero path but end in 2030. To overcome this limitation, we use the onshore wind capacities for 2050 from the EU reference scenario as a lower boundary and multiply these values by a factor of two for an estimated upper boundary for the expected wind expansion (to reflect that increased climate policy ambition likely comes with increased onshore wind capacity). For the example of Germany, this results in a range of 105–210 GW onshore wind capacity, which is in line with a recent review of German net-zero scenarios, finding a range of 74–218 GW (Ariadne 2022).

We draw on the previously described disamenity costs, engineering costs, and turbine placement to derive the cost-potential curve of onshore wind energy, that is, the long-term marginal cost of onshore wind energy as a function of deployment. More precisely, for every turbine that we placed as described in Sect. 2.4, we estimate engineering and disamenity costs from the cost maps defined in Sects. 2.2 and 2.3. Sorting turbines by cost yields the cost-potential curves. Note that the sorting of the turbines is different depending on whether disamenity costs are considered and on their magnitude. The next section describes and analyses the cost-potential curves in more detail.

3 Results

In the following, we will first discuss the results of our model for the example of Germany as Europe's largest country with a high population density (Sect. 3.1). Also using the example of Germany, we will subsequently contrast a disamenity-cost-based turbine placement with enforcing minimum setback distances (Sect. 3.2), before turning toward a comparison of multiple EU countries (Sect. 3.3).

⁷ Note that there is no explicit limitation on the deployment density. In a single unconstrained cell, a maximum of 5 turbines could be placed, implying a maximum of 10 MW/km². Over larger areas, however, the constraints will significantly reduce the (implicit) maximum deployment density.

⁸ https://energy.ec.europa.eu/data-and-analysis/energy-modelling/eu-reference-scenario-2020_en.

⁹ https://energy.ec.europa.eu/data-and-analysis/energy-modelling/policy-scenarios-delivering-european-green-deal_en.

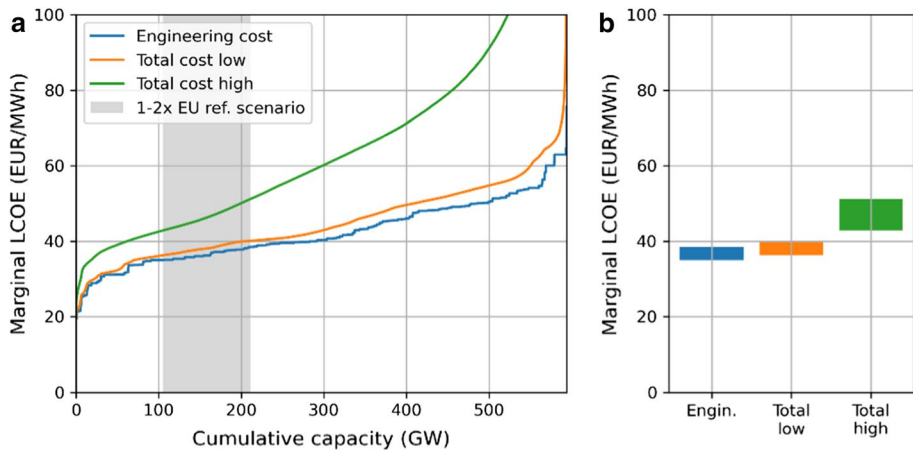
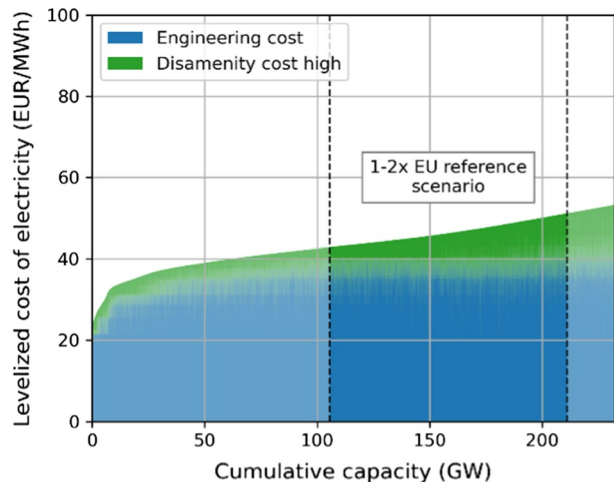


Fig. 5 **a** Cost-potential curves for Germany based on pure engineering costs as well as total costs including low and high disamenity costs, respectively; **b** Corresponding ranges of marginal costs for building 1× (lower bound of boxes) and 2× (upper bound of boxes) the capacity in the EU reference scenario

Fig. 6 Decomposition of the cost-potential curves for Germany for the assumption of high disamenity costs into engineering and disamenity costs



3.1 Example of Germany

In general, we find a small to moderate impact of disamenity costs on total costs, depending on the underlying disamenity cost assumptions. This becomes visible in Fig. 5a, which displays the different cost-potential curves for the example of Germany. Over the entire techno-ecological potential of about 600 GW, the average engineering costs are 42 €/MWh, and the average total costs (engineering+disamenity costs) are 45 and 70 €/MWh for the low and for the high assumption on disamenity costs, respectively. This means that considering disamenity costs leads to an average increase in the total cost of onshore wind energy by 7% to 67%. However, a full exploitation of the technical potential seems both unrealistic and unnecessary. For perspective, we consider an expansion range of one to two times the

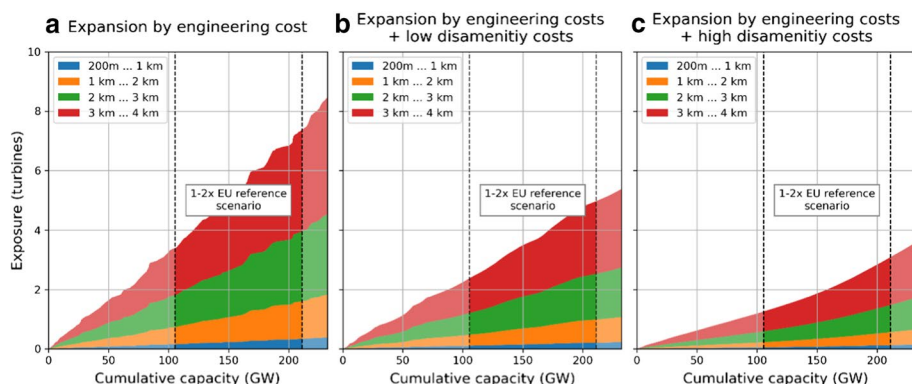


Fig. 7 Number of affected people in Germany within different distances from the wind turbines as a function of wind expansion by **a** engineering cost, **b** total costs including low disamenity costs, and **c** total costs including high disamenity costs

onshore wind capacity in the latest EU reference scenario (grey area in Fig. 5a).¹⁰ Within this expansion range, the marginal costs only increase by 3–5% for the low and by 23–34% for the high assumption on disamenity costs (Fig. 5b). A cost increase in this order of magnitude does not fundamentally threaten the energy transition toward net-zero emissions. Nevertheless, in the case of high disamenity costs, onshore wind energy may become less attractive compared to other decarbonization options, in particular given the steeper slope of the high disamenity cost-potential curve.

Disamenity costs have limited implications on the national level, but they may significantly alter the socially optimal turbine placement within countries. While the engineering cost-potential curve is based on the assumption that turbines in locations with the lowest engineering costs are deployed first, the total cost curves are based on the trade-off between engineering and disamenity costs. Based on the total cost curves, turbines may be built at locations with higher engineering costs due to their lower disamenity costs (Fig. 6). In fact, when building one to two times the onshore wind capacity in the latest EU reference scenario, the average engineering costs increase by about 5% from 32 €/MWh to 34 €/MWh when considering high disamenity costs in the siting of turbines. Note that this is directly related to the energy output of the installed wind capacity: when considering disamenity costs, turbines are placed at less windy locations, producing about 5% less energy. The difference between this increase in engineering costs and the larger increase in total costs discussed in the previous paragraph are the actual disamenity costs after optimizing turbine placement for total cost.

When considering disamenity costs in the cost-potential curves, turbines are built further away from population centers leading to a lower exposure of inhabitants to turbines. This is illustrated in Fig. 7, which displays the average number of turbines to which inhabitants in Germany are exposed when expanding wind energy according to the different cost-potential curves. When expanding wind energy up to one to two times the capacity in

¹⁰ We consider this range to reflect that the EU reference scenario does not meet the net-zero emission target defined in the EU Green Deal and that increased climate ambition likely comes with more onshore wind capacity (see Sect. 2.4).

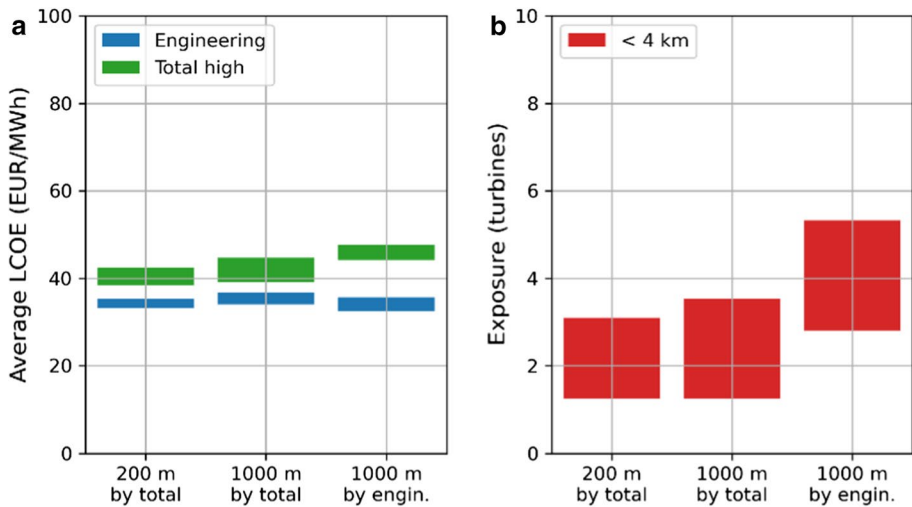


Fig. 8 Average costs and turbine exposure in three different deployment scenarios for Germany reaching 1× (lower bound of boxes) and 2× (upper bound of boxes) the capacity of the EU reference scenario. Wind turbines are deployed using either a 200 m or 1 km minimum setback distance to settlements and either following minimal engineering costs or minimal total costs. **a** Ranges of average engineering and total costs and **b** average turbine exposure within a 4 km radius

the EU reference scenario purely by engineering costs, residents are exposed to an average of 3.4 to 7.4 wind turbines, respectively, within 4 km distance from their homes. When considering the low assumption for disamenity costs in the least-cost turbine placement, this number is reduced by more than 30% to 2.4 to 5.0 turbines. The average exposure is cut by more than 60% to 1.3 to 3.1 turbines in the high disamenity cost case. For the example of Germany, this means that considering disamenity costs in the placement of turbines could reduce the number of affected people by more than 60% at an increase in engineering cost of only 7%.

3.2 Enforcing Setback Distances

In our main scenario, we apply a minimum setback distance of 200 m for wind turbines to settlements mainly for technical and safety reasons. The attractiveness of locations close to settlements is determined entirely by disamenity and engineering costs. Many jurisdictions in Europe require larger minimum distances of 1 km or more (McKenna et al. 2022), mostly motivated by the desire to reduce disamenity cost. To assess the usefulness of such larger setback distances, this subsection compares our main scenario with 200 m setback distance to two sensitivity runs applying a setback distance of 1 km (changing the respective parameter in GLAES, see Sect. 2.4). While our main scenario and the first sensitivity build turbines by their total costs (considering disamenity costs), the second sensitivity run builds turbines by their pure engineering cost (ignoring disamenity costs). Throughout this section, we restrict the analysis on the assumption of high disamenity costs as a conservative estimate.

Our results show that larger setback distances increase total costs without reducing the overall exposure to wind turbines. When the minimum setback distance of 200 m

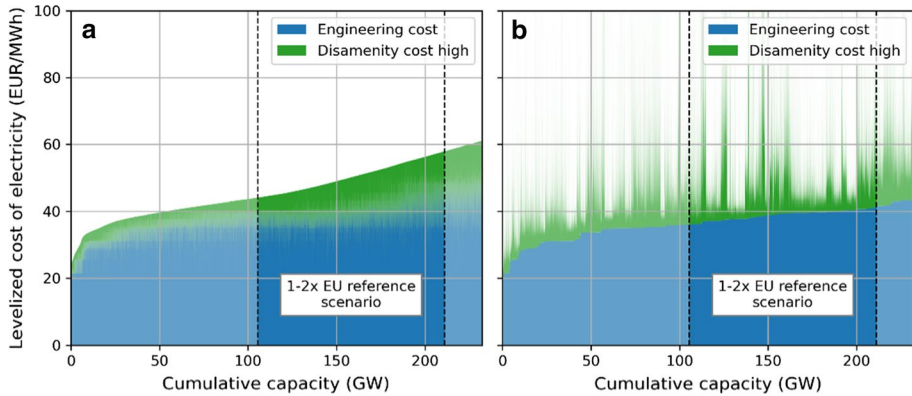


Fig. 9 Decomposition of the cost-potential curves for Germany into engineering and disamenity costs (high assumption) **a** for turbine placement with only 1 km minimum distance from settlements considering high disamenity costs compared and **b** for turbine placement with 1 km minimum distance from settlements not considering disamenity costs in turbine placement

is increased to 1 km, the techno-ecological potential is reduced from about 600 GW to 380 GW. When still considering disamenity costs in the turbine placement, total costs to reach one to two times the capacity of the EU reference scenario increase by 2 to 5% (Fig. 8a). This is because the strict 1 km setback distance excludes turbine locations that were chosen based on their low total cost, and they need to be replaced by turbines with higher total costs. While the setback distance naturally avoids turbine exposure within a 1 km radius, the exposure in the 1 to 4 km range remains constant when building the capacity of the EU reference scenario and even increases by 14% when building twice as much, compared to building the same amount of capacity with only 200 m setback distance (Fig. 8b). Apparently, some of the locations which are excluded because of the 1 km setback difference affected less people than the locations chosen instead. As a result, disamenity costs also increase. Note that our analysis is for specific wind capacity targets. For a target in energy terms, costs will increase even further because larger setback differences exclude some of the locations with the best resources (see also Mai et al. 2021).

Using the larger setback distance and considering only engineering costs in the turbine placement worsens results further. The total costs to reaching one to two times the capacity of the EU reference scenario increase by 13–15%, and turbine exposure rises by 70–120% (Fig. 8). In isolation, a setback distance of 1 km is an ineffective means to decrease disamenity costs of and exposure to wind turbines. Figure 9 illustrates the cost-potential curves in the two sensitivity runs. In the first sensitivity run (Fig. 9a), the cost-potential curve becomes much steeper than in the main scenario (Fig. 6), and the marginal cost increase even more than the average cost displayed in Fig. 8. In the second sensitivity run (Fig. 9b), it becomes apparent that a purely engineering-cost-based turbine placement means that some turbines will lead to very high disamenity costs, despite the implemented 1 km minimum setback distance.

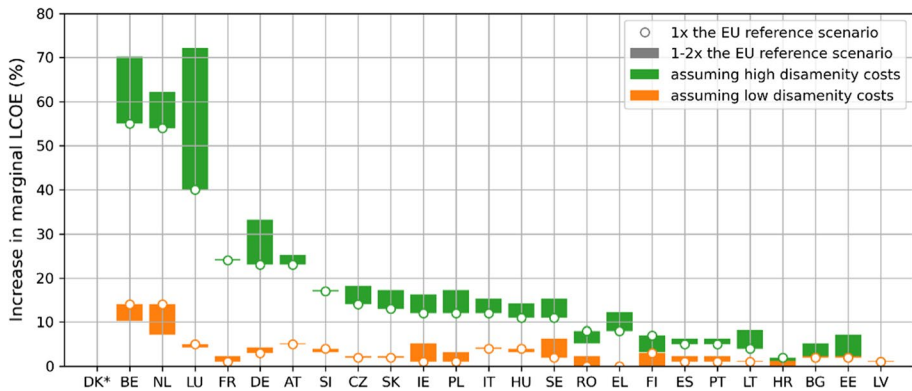


Fig. 10 Increase in the marginal LCOE due to high (upper boxes) and low (lower boxes) disamenity costs, when building 1× (circles at one end of the boxes) and 2× (other end of the boxes) the capacity in the EU reference scenario. See footnote 9 for more information on Denmark

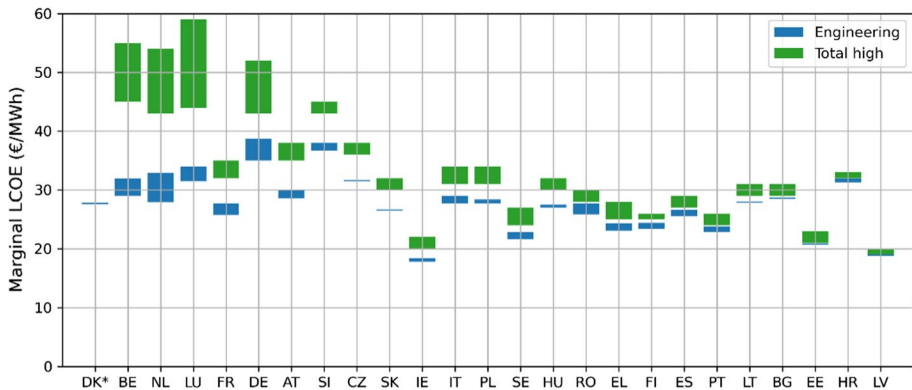


Fig. 11 Marginal engineering and total costs when building 1× (lower bound of boxes) and 2× (upper bound of boxes) the capacity in the EU reference scenario; countries are sorted by the relative increase in LCOE due to high disamenity costs (Fig. 10). For Denmark, the marginal engineering LCOE at full exploitation of the potential is displayed (total cost exceed the graph)

3.3 Cross-Country Comparison

After the previous focus on the example of Germany, this section broadens the perspective towards all EU countries (except for the islands of Malta and Cyprus). How relevant are disamenity costs for wind energy across Europe, given the different techno-ecologic potential, the targeted buildout, and population distribution? Like Sect. 3.2, this session focuses on the results for our high assumption on disamenity costs as a conservative estimate.

We find that the increase in the national marginal LCOE when considering disamenity costs is quite different across countries (Fig. 10). Denmark represents a special case because its capacity target in the EU reference scenario exceeds the available potential.¹¹

¹¹ If we assumed that the full potential was deployed, the effect of disamenity costs would exceed the graph, because locations with very high disamenity costs could not be avoided. This highlights the value of flexibility in turbine placement for reducing disamenity costs.

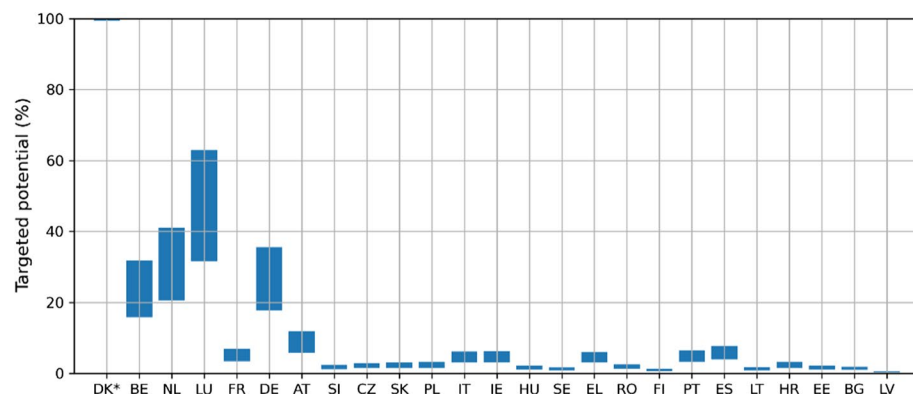


Fig. 12 Marginal engineering and total costs when building 1× (lower bound of boxes) and 2× (upper bound of boxes) the capacity in the EU reference scenario; countries are sorted by the relative increase in LCOE due to disamenity costs (Fig. 10). For Denmark, the EU reference scenario exceeds the technical potential

Apart from this special case, Belgium, the Netherlands, and Luxemburg show the highest increase (up to 55% at 1× the EU reference scenario), followed by France, Germany, and Austria (about 23% increase at 1× the EU reference scenario). For most countries, however, disamenity costs have a smaller relative effect (10–20% for eight countries and <10% for the remaining ten countries). Country differences increase further when the onshore wind capacity is increased from one to two times the EU reference scenario, because for some countries, the relative impact of disamenity costs increases substantially (e.g., BE, NL, LU, DE), while the relative impact is almost constant for others (e.g., FR, AT, SI, ES, PT, HR, LV).¹² Such a heterogeneity in the relative effect of disamenity costs is a first indication that incorporating disamenity costs in energy system models may change the optimal regional distribution of onshore wind energy as well as its relevance compared to other energy sources, such as solar photovoltaics.

Further insights can be drawn from assessing the effect of disamenity costs in absolute terms (Fig. 11). Overall, the absolute impact of disamenity costs is below 15 €/MWh in most countries, except for the Benelux region, where the impact raises up to 25 €/MWh for large expansion scenarios. Furthermore, disamenity costs lead to an increase the inter-country variability of wind onshore LCOE (from 18–38 to 19–59 €/MWh), which could make inter-country re-allocation of wind energy more attractive. In addition, it becomes apparent that countries with a high relative effect of disamenity costs (displayed in the left of Fig. 11) tend to have high engineering costs in the first place. Finally, some countries change their relative competitiveness. For instance, marginal engineering costs in Poland are cheaper than in Bulgaria, but Bulgaria is cheaper in terms of total costs.

¹² In exceptional cases, the relative impact of disamenity costs decreases with wind capacity expansion (RO and FI). However, a closer look at the data revealed that the absolute impact of disamenity costs is almost constant, and the relative impact only decreases because the baseline engineering costs increase.

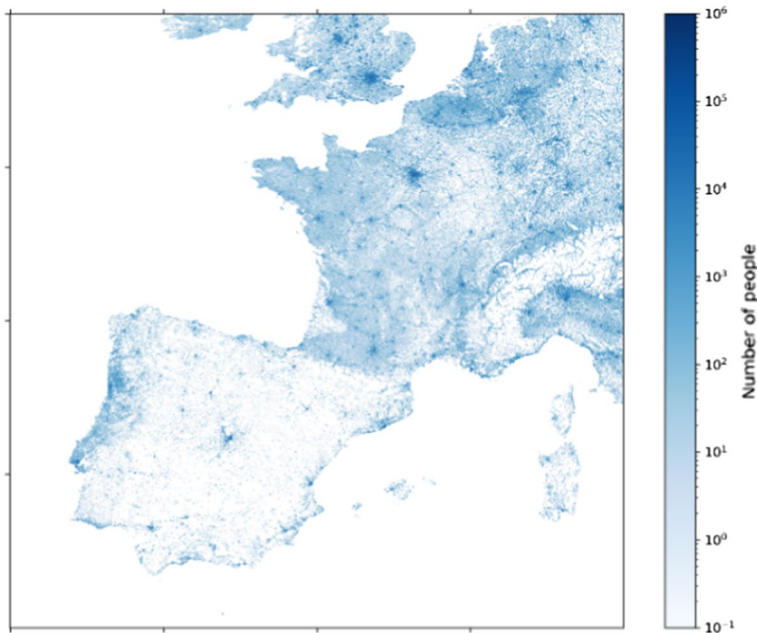


Fig. 13 Map of population in South-Western Europe (inhabitants per km²). While the population in France is very dispersed, it is very concentrated in Spain

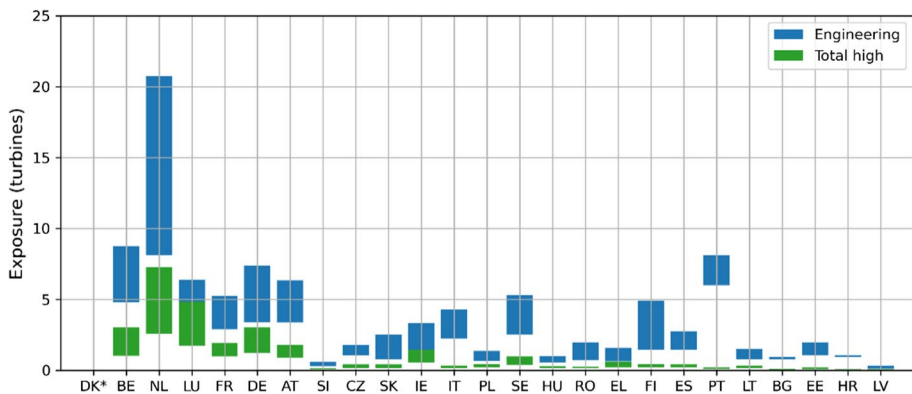


Fig. 14 Population's exposure to installed wind turbines within 4 km distance when building 1× (lower bound of boxes) and 2× (upper bound of boxes) the capacity in the EU reference scenario; countries are sorted by the relative increase in LCOE due to disamenity costs (Fig. 10)

Part of the above can be explained by the targeted potential, that is, the share of the techno-ecologic potential corresponding to one to two times the capacity target in the EU reference scenario (Fig. 12). Again, the situation is very mixed across EU countries, because differences in both the available potential and the targeted expansion. The countries that were earlier found to have high disamenity costs and a steep increase in disamenity costs with further wind expansion are those countries with ambitious expansion targets

relative to the national potential (BE, NL, LU, DE). By contrast, countries with similarly high disamenity costs but with a lower sensitivity to expansion have less ambitious target relative to the available potential (FR, AT). This is plausible as exploiting only a small share of the potential leaves a large degree of flexibility to avoid locations with high disamenity costs. Conversely, a high target share leads to a reduced flexibility.

Some differences in the disamenity costs, however, cannot be explained by the targeted potential. For example, effect of disamenity costs is much smaller in Spain than in France, although their targeted potential and their average population densities (94 cap/km² in Spain and 106 cap/km² in France¹³) are similar. The cause for the difference in disamenity costs appears to be the spatial distribution of the population. Settlements are very dispersed in France and, therefore, disamenity costs can hardly be avoided. Whereas population is very concentrated in Spain and onshore wind energy can easily be built in remote areas (Fig. 13).

The heterogeneity that we find between EU countries is also reflected in the population's exposure to wind turbines and in exposure reduction when considering disamenity costs in the turbine placement (Fig. 14). For example, Belgium, the Netherlands, and France exhibit similar characteristics to Germany, with about 60% reduction in exposure when considering disamenity costs. By contrast, other countries such as Italy, Sweden, Finland, Spain, and Portugal show a much higher reduction by up to 98%. The size of the reduction generally reflects how much flexibility there is for turbine placement. Furthermore, the initial exposure is driven by the coincidence of windy sites with densely populated areas, and the remaining exposure is highly correlated with the relative effect of disamenity costs on total costs (Fig. 10).

4 Discussion

We estimated the effect of disamenity costs on cost-potential curves across 25 EU countries. Because estimates of disamenity costs are highly uncertain, we consider a range of plausible assumptions. For the lower end of this range, we show that disamenity costs are negligible and hardly affect the placement of turbines. For the upper end of the estimates, disamenity costs are high enough to induce substantial changes in turbine placement within countries. For the example of Germany, we show that higher minimal distances between turbines and settlements increase the disamenity costs, because it reduces the flexibility to explicitly trade-off disamenity costs and wind potential. This also explains some of the substantial heterogeneity we find between different EU countries: those countries that target to exploit a higher share of the national techno-ecological potential are likely to feature higher disamenity costs. Other influencing factors are the distribution of the population and the correlation between windy and densely populated areas.

Many of the required input assumptions are subject to substantial uncertainty, and all our results should be read accordingly. In addition to the uncertainty about the parametrization of disamenity costs, people's utility may also depend on how fair they perceive the distribution of wind turbines, which is not captured in our analysis (see Sect. 2.1). Furthermore, there is uncertainty regarding the land eligibility for turbine placement. We build on the internationally representative parameters recommended by Ryberg et al. (2018), but

¹³ Eurostat dataset DEMO_R_D3DENS.

local conditions can vary substantially, and these conditions may change dynamically in the future. Besides, land eligibility restrictions in practice are often not binary as assumed in our modeling suggested in our current model, but exceptions can lead to turbine placement within theoretically ineligible areas (Hedenus et al. 2022). Such exceptions could allow turbine placement to respond even more to disamenity costs than in our analysis, especially as many of these theoretically ineligible areas will be scarcely populated.

We focused on the impact of disamenity costs on the marginal cost of onshore wind energy and on the turbine placement within countries. From the moderate size of the cost increase, it can already be seen that wind energy will remain a cornerstone of a cost-optimal transition toward net-zero emissions. However, the increase in the marginal costs may reduce the competitiveness of wind energy compared to other decarbonization options, such as solar photovoltaics and energy efficiency. In addition, the heterogeneity of disamenity costs across European countries may change the international distribution of onshore wind energy. Answering these more nuanced questions would require an energy system model, which is beyond the scope of the current study. We hope, however, that the dataset published with this study will enable such an analysis in the near future.¹⁴

One objective of this study is to provide a European dataset on disamenity costs to the energy modeling community, as well as the scripts to tailor this dataset to individual needs and assumptions. Nevertheless, some public policy aspects are worthwhile to be discussed.

In this regard, it should first be acknowledged that real-world turbine placement does not follow a cost-optimization model. Instead, it is determined by regional planning, zoning laws, permitting procedures, regulation of protected areas, distance rules, and (local) politics. As regional planning is a complex process that takes into account multiple objectives, it may be argued that it already accounts for disamenity costs—albeit possibly in crude and biased ways.

To the extent that our specification of disamenity costs is accurate, economic theory would suggest that a first-best internalization policy would be a differentiated Pigouvian tax, where turbine developers would pay a fee for each turbine built that follows Eq. (1). Such a tax would yield the first-best allocation of turbines that minimizes social costs (Fig. 6), where an absence of such policy and proxy policies yields sub-optimal siting and hence higher costs (Fig. 9b).

Our economic analysis of disamenity costs is agnostic about whether such a Pigouvian tax exists. Furthermore, it is agnostic about whether the affected citizens are actually compensated. From a social cost perspective, the disamenity costs would occur anyways, and it would always make sense to consider disamenity costs in the turbine placement to maximize welfare (be it through a Pigouvian tax or regional planning). By contrast, a compensation mechanism would address the political question about how to distribute these welfare gains. In this regard, a smart payment mechanism could be desirable to increase the public acceptance of onshore wind energy.

¹⁴ For an indication on the impact of the cost of onshore wind energy on energy scenarios, readers may refer to Neumann and Brown (2021). Depending on the baseline costs, a 10% cost increase may reduce the deployment of onshore wind energy by 5–20% (median values with regard to other parameter uncertainty).

5 Conclusions

We show that disamenity costs play only a minor role for the expansion of onshore wind energy in Europe. Only in four countries with high population densities and only if we assume the uncertain disamenity cost to be high do we see large increases in the marginal LCOE of onshore wind. In the other countries or when uncertain disamenity cost are low, increases in the marginal LCOE are low or negligible. Our results indicate that disamenity costs will not be a major hurdle for the expansion of wind energy in Europe.

However, even low increases in the marginal LCOE could lead to changes in the design of energy systems in the following two ways. First, considering disamenity costs can make wind sites with low population density attractive despite relatively low wind speeds, as the avoided disamenity costs can compensate for the higher engineering costs. In many cases, a disamenity-cost-optimized turbine placement reduces exposure strongly without increasing total cost much. Second, considering disamenity costs can make wind energy less competitive against other generation technologies, in particular solar energy, and could therefore lead to smaller shares of wind energy. Energy system models that can or want to incorporate this level of granularity need to integrate disamenity costs to be able to represent these effects. Our openly available result data allow to do that.

With regard to public policy, we conclude that an explicit consideration of disamenity costs in an optimized turbine placement is more effective than minimum setback differences between wind turbines and populated areas. In fact, minimum setback difference can even be counter-productive as they reduce the flexibility for an optimized trade-off between disamenity costs with engineering costs.

We have focused on disamenity costs on nearby human population as one important component of social costs that is often neglected in energy models. Further research may widen the scope to internalize further cost components such as negative effects on landscape scenicness as well as wildlife. Despite all uncertainty about these cost components, this may yield a more appropriate approximation of the overall social costs of onshore wind power to be included in future energy system analyses.

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Data availability The code used for the presented analysis as well as the generated data is published under a CC-BY license. The code is implemented in Python, hosted on GitHub (<https://github.com/timtroendle/wind-onshore-cost-potential>), and archived on Zenodo (<https://doi.org/10.5281/zenodo.7362048>). The workflow that generates the output is coordinated using the Snakemake package (Mölder et al. 2021) and includes multiple steps: (i) automatically downloading required input data, (ii) re-calculating results of other research groups, (iii) aggregating and combining population and cost data, and (iv) performing final analyses and visualizations. Researchers can recreate the presented results as well as customize the underlying assumptions. For example, different disamenity cost assumptions may be implemented by adjusting the underlying Python function. While the code offers the possibility to flexibly adjust our analysis, we also provide a ready-to-use dataset. This dataset is published on Zenodo (<https://doi.org/10.5281/zenodo.7361513>) and includes: (i) maps that exhibit the population count within a predefined distance and the resulting local disamenity costs, and (ii) tables that summarize the engineering and disamenity cost faced at each potential turbine location in the EU. The published datasets can be used by researchers that want to build on the presented findings, or that want to use the generated data directly. For example, modelers can use the tables to refine the representation of wind onshore cost potential curves in power system models.

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