Scenicness assessment of onshore wind sites with geotagged photographs and impacts on approval and cost-efficiency

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Abstract

Cost-efficiency and public acceptance are competing objectives for onshore wind locations. The impact of scenicness on these two objectives has been difficult to quantify for wind projects. We analyse the link between economic wind resources and beautiful landscapes with over 1.5 million 'scenicness' ratings of around 200,000 geotagged photographs from across Great Britain. We find evidence that planning applications for onshore wind are more likely to be rejected when proposed in more scenic areas. Compared to the technical potential of onshore wind of 1700 TWh at total costs of £280 billion, removing the 10% most scenic areas implies about 18% lower generation potential and 8-26% higher costs. We consider connection distances to the nearest electricity network transformer for the first time, showing that the connection costs constitute up to half of the total costs. The results provide a quantitative framework for researchers and policymakers to consider the trade-offs between cost-efficiency and public acceptance for onshore wind.

Locating onshore wind farms implies a tension between cost-efficiency and public acceptance. In the British context adopted for this research, onshore wind was until very recently not eligible for subsidies.[1] Yet onshore wind has very high approval ratings, as highlighted by some recent surveys. Overall support for renewable energy reached its highest ever level of 85% in 2018, increasing from 79% in 2017.[2] Similarly, a YouGov[3] survey in 2018 found general support for onshore wind technology.

Despite this general approval, onshore wind encounters local opposition from planning authorities and local communities, referred to by Bell et al.[58] as the 'social gap', especially if they are not directly engaged in the planning processes[4,5]. Visual impact is one of the central arguments from local residents against onshore wind installations[6,7,8], although concern is reduced when people live further away from turbines[8,9] and in contexts where the affected people have previous experience with wind energy.[10,11,12,13] A prominent example is the Scout Moor wind farm in Lancashire, England, consisting of 26 2.5 MW turbines. The rejection in 2017 of the planning application to add 16 additional turbines emphasized the "valued landscape because of its openness, tranquillity and attractive views into the lower valleys".[1]

The remoteness of aesthetically-appealing landscapes could also be a key cost factor. Rural locations tend to be considered more scenic[24], and average wind speeds tend to be higher in rural locations, due to a generally lower surface roughness and steeper velocity gradients.[25] However, rural areas are likely to have an increased distance from the electricity network than suburban or urban locations, hence higher grid connection costs. These represent one component of the so-called system costs of renewable energies, which also include the so-called profiling costs due to controllable power plants having to modulate their output, and balancing costs due to the inaccuracy in forecasts and needs for the system to provide short-term flexibility.[26,27]

The apparent conflict between public desire to conserve beautiful landscapes and economic onshore wind resources (i.e. high average wind speeds) has been considered in a number of studies[4-13]. However, a quantitative examination of this trade-off has not previously been possible, due to a lack of national-scale data on scenic value. Furthermore, this link is typically not considered in resource assessments for renewable energy technologies. Instead, these studies tend to calculate a technical generation potential along with costs, which are employed by researchers and policymakers to analyze future energy scenarios.[14,15] These resource assessment methods have recently been improved by developing open source methods[16], employing more accurate data[17,18] and considering non-technical and especially social constraints[19,20,21] including the visual impact of renewable technologies on the landscape.[22,23] Yet none of these previous studies has quantified the trade-off between public valuations of the landscape and the cost of onshore wind at the national scale. The methods section gives a precise definition of public acceptance in this context.

Against this background, this paper presents a quantitative spatial framework to explore the tension between landscape beauty (scenicness) and cost-efficiency for onshore wind. This means connecting the aesthetic quality of the landscape with the quality of the wind resource to address the following three research questions: Is scenicness already implicitly considered in planning practice for onshore wind? How is scenicness related to onshore wind resources, if at all? What is the impact of scenicness on the costs and potentials of onshore wind? To find answers, we conduct a statistical and geospatial analysis of planning applications for onshore wind alongside national data on scenic value, and a techno-economic wind resource assessment. We show that onshore wind applications are less likely to be accepted in more scenic areas, but that energy generation potential decreases and costs rise if the most scenic areas are protected. Our results suggest that compromises between the partly competing objectives of maintaining beautiful landscapes and developing low-carbon energy must be met, and offer a framework to help policymakers navigate these trade-offs.

Landscape beauty and planning application outcomes

To study the association between the scenicness and the planning outcome of energy projects, we use two main data sources as outlined in the methods section. First, we measure scenicness using crowdsourced scenic ratings from *Scenic-Or-Not* (http://scenicornot.datasciencelab.co.uk/) available at 1 km^2 resolution for the whole of Great Britain. *Scenic-Or-Not* presents users with random geotagged photographs, most of which have been taken at eye level. Users are asked to rate the photographs on an integer scale of 1–10, where 10 indicates “very scenic” and 1 indicates “not scenic”. The photographs are sourced from *Geograph* (http://www.geograph.org.uk), a moderated web-based project that aims to collect and reference geographically representative images of every square kilometre of the British Isles. Here, we analyse the mean scenicness values for all photos rated three times or more. The final *Scenic-Or-Not* database covers nearly 95% of the 1 km squares of land mass in Great Britain and contains 1,536,054 ratings for 212,212 images (Figure 1).

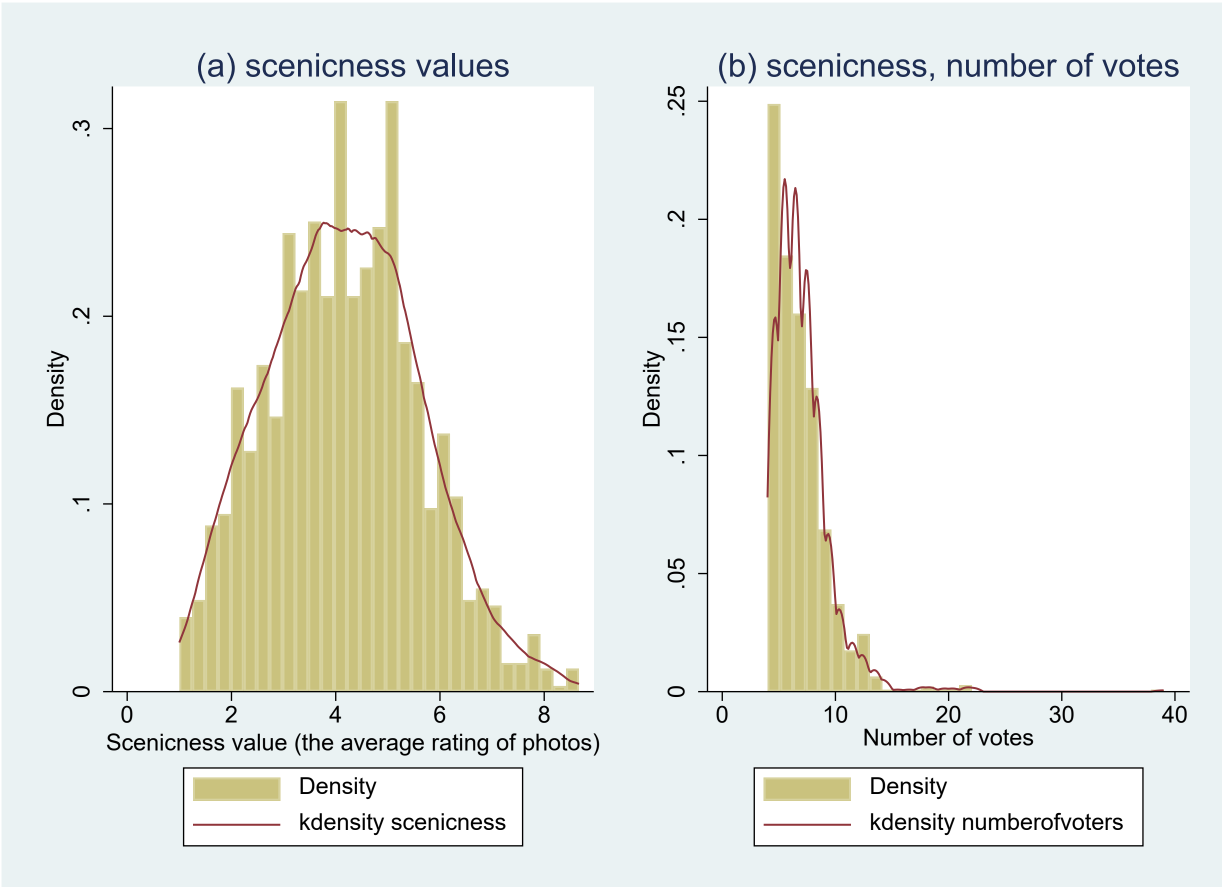

Figure 1 | Frequency distributions of scenicness values and number of votes
Number of observations is 1324; kernel = epenechnikov, for scenicness values bandwidth = 0.3134 and for number of voters bandwidth = 0.4795.

The second primary data source is the Renewable Energy Planning Database, which contains detailed data about renewable energy applications in Great Britain.[28] For all locations within this database, five different variables are computed: distance to the closest Special Areas of Conservation (SAC), distance to the closest Special Protection Areas (SPA), distance to the closest Ramsar areas (wetlands), distance to the closest National Park, and distance to the closest airport (Table 1).

The logit regression outlined in the methods section employs this data to fit five different models between the given independent variables and the planning application outcome. Table 2 shows the results, whereby model 1 includes only the scenicness value, whereby the associated estimated odds ratio is below one (estimated coefficient is negative) and significant (sensitivities are shown in Table 3 and discussed in the method section). In the following models 2-4 we sequentially introduce the year fixed effects, the project size, and the environmental variables respectively, and in model 5 we exclude the scenicness value. The estimated odds ratio associated with the scenicness value remains below one and significant in all specifications. Due to the AIC values and the Akaike weights, model 4 is our preferred specification, whereby the odds ratio associated with the scenicness value is estimated at 0.781 (std.err. is 0.037). For every one unit increase in the scenicness value, we expect a 22% decrease in the odds of a positive application decision, all else being equal. The marginal effect is -0.06, i.e. an application with 1% higher scenicness value has 6% lower probability to be evaluated positively. In the Scout Moor example mentioned above, the maximum scenicness value in the vicinity was 7.2, i.e. within the top 10% of most scenic locations in the dataset (see methods section for details).

Table 1 | Descriptive statistics of Renewable Energy Planning Database, with positive and negative application decisions

	Positive application decision mean = 0.57, n=756		Negative application decision mean = 0.43, n=568	
	Mean	Std. dev.	Mean	Std. dev.
Scenicness value (the average rating of photos)	4.005	1.517	4.351	1.373
Number of votes	6.811	2.824	6.752	2.441
Capacity (MW)	19.268	34.041	17.654	33.778
Number of turbines	9.503	13.643	6.773	10.203
Dist. to the closest airport (km)	39.890	23.393	41.474	34.230
Dist. to the closest Special Area of Conservation (SAC) (km)	7.653	6.754	7.878	7.359
Dist. to the closest Special Protection Area (SPA) (km)	93.134	106.948	76.244	87.688
Dist. to the closest Ramsar area (km)	19.656	17.516	18.961	16.630
Dist. to the closest National Park (km)	52.644	47.639	41.474	34.230

Notes: number of observations is 1324.

Turning to the other results, several general observations can be made. First, a larger number of wind turbines is associated with an increase in the probability that a planning application would be accepted, whereas larger project capacity is associated with a small decrease in the probability of acceptance. Harper et al.[30] also find a positive correlation between the number of turbines and the positive application outcome, and Roddis et al.[31] find the negative associations between project capacity and the positive outcome of the project application. Both variables account for the technical characteristics of the projects and are to some degree proxies for the scope of the projects. They are in our case jointly significant ($\chi^2(1) = 67.64, p < 0.001$), which implies that projects with more wind turbines are more likely to be approved, for a given capacity and the other included variables.

Table 2 | Logit regression results (odds-ratio) for wind project planning outcomes, showing five models of increasing explanatory power

	Model 1	Model 2	Model 3	Model 4	Model 5
Scenicness value	0.850***	0.793***	0.769***	0.781***	
	(0.033)	(0.034)	(0.036)	(0.037)	
Number of turbines			1.231***	1.228***	1.221***
			(0.031)	(0.031)	(0.030)

	Model 1	Model 2	Model 3	Model 4	Model 5
Capacity (MW)			0.934***	0.935***	0.935***
			(0.008)	(0.008)	(0.008)
log distance to the closest National Park				1.173***	1.215***
				(0.068)	(0.069)
log distance to the closest airport				0.988	0.943
				(0.112)	(0.105)
log distance to the closest Special Protection Areas (SPA)				0.965	0.919**
				(0.042)	(0.039)
log distance to the closest Special Areas of Conservation (SAC)				0.889*	0.906
				(0.054)	(0.054)
log distance to the closest Ramsar areas				1.028	1.039
				(0.061)	(0.061)
Year fixed effect	no	yes	yes	yes	yes
Constant	2.626***	1.296	1.668	1.634	0.822
	(0.449)	(1.610)	(2.122)	(2.249)	(1.137)
Number of observations	1,324	1,324	1,324	1,324	1,324
AIC	1,794.50	1,536.51	1,426.08	1,425.27	1,450.73
Akaike weights	3.99E-81	4.19E-25	4.00E-01	6.00E-01	1.78E-06
Log likelihood	-895.25	-751.26	-694.04	-688.63	-702.36

*Note: discrete dichotomous variable taking a value of 1 if the application decision is positive, otherwise 0; ***, **, * indicate that estimates are significantly different from zero at the 0.01, 0.05 and 0.10 levels, respectively; standard errors are in parentheses. AIC is Akaike's[29] information criterion. Akaike weights can be interpreted as the probability that a model is the best model, given the data and the set of candidate models.*

Potential electricity generation and costs of onshore wind

Many studies have analysed the potential and associated costs for onshore wind in Great Britain, leading to a range of estimates based on different assumptions. Most employ the Levelized Costs Of Electricity (LCOE), which relate the costs over the lifetime of the plant to one unit of electricity generated. Remote locations could mean long distances from the electricity network, which is why we also assess the connection costs to the nearest transformer. In this context, a wind polygon is a suitable area for onshore wind plants, with space for one or more turbines, derived as outlined in the methods section. We thereby differentiate between the following four scenarios (for details see the methods section): 1) Individual wind polygons without network connections, *Turbine_no_conn;* 2) Individual wind polygons with individual network connections to the nearest transformer, *Turbine_conn;* 3) Wind polygons clustered into wind parks with network connections to the nearest transformer, based on the maximisation of the energy yield, *Wind_parks_EYield* – employed here as the "reference" scenario as considered most realistic; and 4) Wind polygons clustered into wind parks with network connections to the nearest transformer, based on the minimisation of the LCOEs, *Wind_parks_LCOE.*

To analyse the impact of grid connection costs, we first determine and economically assess potential locations and capacities for onshore wind following an extended version of the methodology introduced by McKenna et al.[34], and then compute the additional costs to connect these to the nearest transformer (Figure 2).

Figure 3 shows the cumulative generation potential and cumulative costs associated with realizing this potential in the four analysed scenarios, for locations with

LCOEs < 1 £/kWh. The gradient of the curve can be interpreted as the marginal cost in £/kWh to realise one additional unit of generation potential. The maximum potential shown for each scenario is what would be achieved if all suitable land were used for wind farms. The flattest curve is the one relating to *Turbine_no_conn*, with total potentials and costs of 1350 TWh and £ 90 billion respectively. At the other extreme is the *Turbine_conn* case, resulting in over £ 1470 billion costs and around 1610 TWh generation potential.

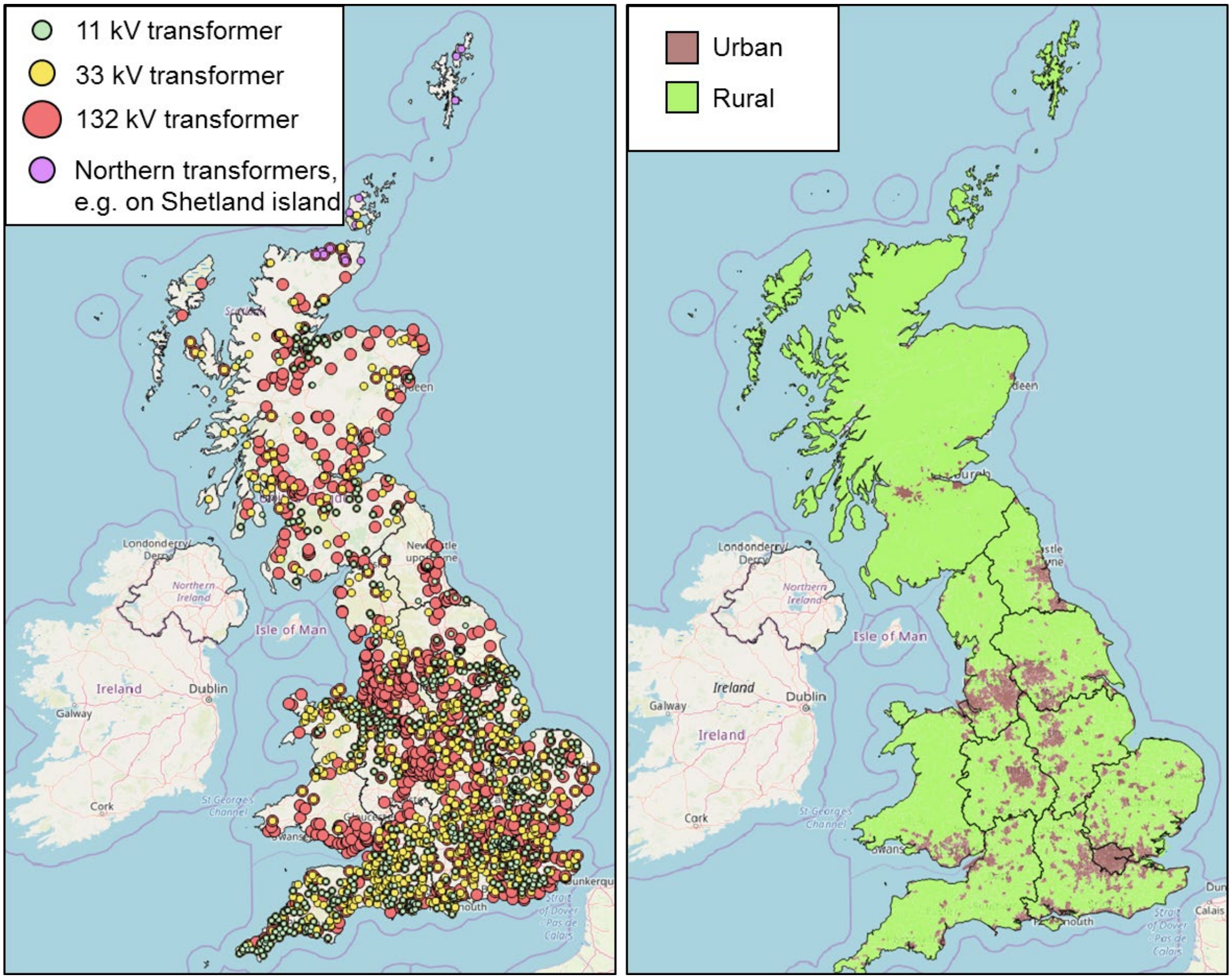

Figure 2 | Transformers tagged in OpenStreetMap and urban and rural area classifications in Great Britain. The comparison of the locations of transformers (left part of figure) and urban areas (brown shapes, right part of figure) shows, that those transformers are predominantly located in or near urban areas. Base maps are from OSM[53] and ONS[66], as detailed in the text.

The difference in the results of these two scenarios is due to considering the connection costs, which for a given available area tend to increase the LCOEs. Roughly half-way between these two extreme scenarios are the arguably more realistic scenarios, in which the wind polygons are clustered into wind farms and these are connected to the nearest transformer. Both of these scenarios exhibit similar gradients, with overall costs and potentials at around 1400 TWh and £ 210 billion in the case of *Wind_parks_LCOE*, and 1720 TWh and £ 280 billion in the case of *Wind_parks_EYield* respectively. Comparing the latter scenario with the scenario without connections (*Turbine_no_conn*) reveals an approximate difference in total costs of £ 190 billion to realize the full potential.

Expressed as a marginal cost, this equates to a difference between £ 0.16 billion/TWh (*Wind_parks_EYield*) and £ 0.06 billion/TWh (*Turbine_no_conn*). In other words, the marginal and total costs per TWh more than double if network connection costs are considered.

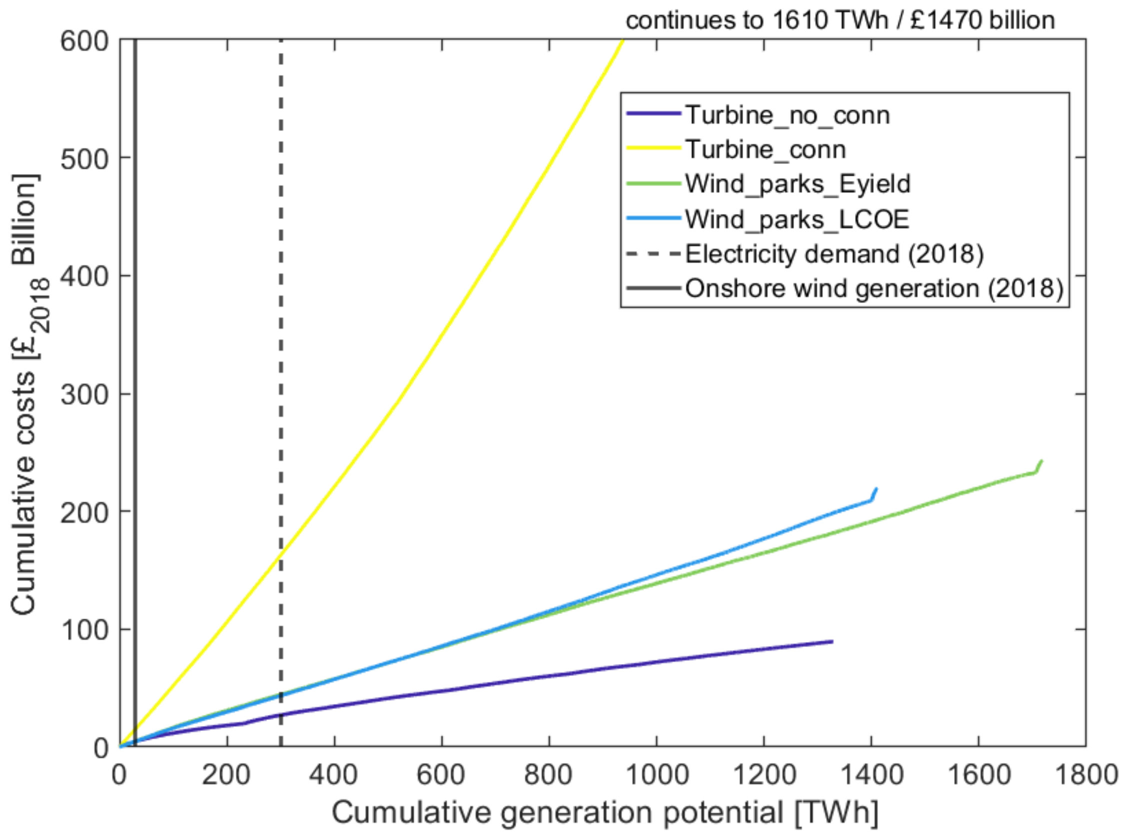

Figure 3 | Cumulative costs and electricity generation potentials of onshore wind in Great Britain. We illustrate the results from four analysed scenarios, with and without network connections costs. We also depict Great Britain's national electricity demand[32] **and electricity generation from onshore wind in 2018**[33]**. The end of the curve for *Turbine_conn* is at about 1610 TWh and £ 1470 Billion.**

The results of this study are in broad agreement with the literature. In terms of total suitable area, we identified 33% of Great Britain's land area, somewhat higher than Ryberg et al.[16] who found 28% and McKenna et al.[34] with 21%. The latter found total costs of about € 70 billion (about £ 50 billion at then-current rates) for around 1270 TWh (or 470 GW), which corresponds well with the *Turbine_no_conn* scenario here. In our base case (*Wind_parks_EYield*), we determined 1700 TWh and 760 GW as the generation potential and installed capacity respectively. This is relatively high compared to McKenna et al.[34], but much closer to the more recent study of Ryberg et al.[35], who found 2260 TWh and 690 GW potential. The only other recent study to analyze Great Britain[14] concluded a very modest 220 GW potential in its reference scenario, up to 421 GW in the high case. These deviations between studies are mainly due to different technical and geographical assumptions.[36]

Implications of scenicness for onshore wind potentials

Building on the preceding two sections, we here explore the implications of scenicness in two central scenarios. To facilitate interpretation of the results, we firstly focus on one scenario (*Wind_parks_EYield*) and present the cost-potential curves for quartiles of the scenicness distribution, as well as the maximum value (i.e. 10). We present the minimum, mean and maximum generation from six diverse wind years in Figure 4. The distribution of LCOEs is similar in all four shown sets of curves, but the cumulative generation potential at LCOEs less than 1 £/kWh ranges from just 363 TWh with scenicness values of up to 3.67, to 750 TWh up to 4.67, to 1173 TWh up to 5.8, and finally to 1700 TWh up to 10.

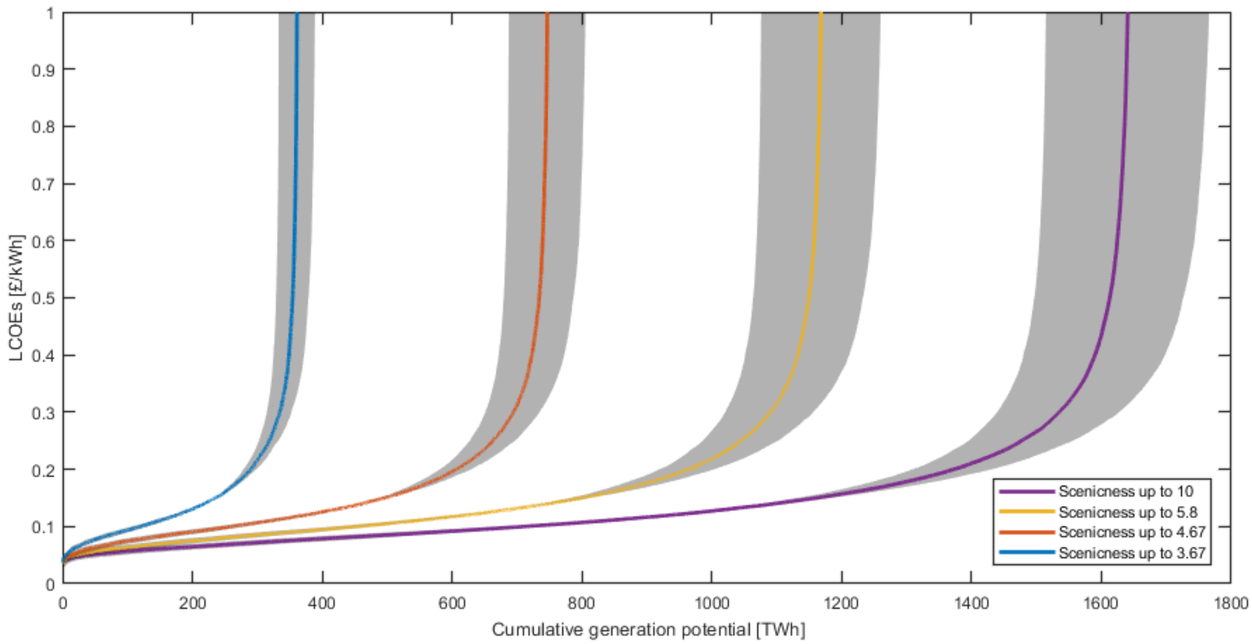

Figure 4 | Cost-potential curves for four scenicness thresholds 3.67, 4.67, 5.8 and 10 in Great Britain. The solid lines show the means and the grey thresholds show minimum and maximum ranges for the wind years of 2001-2006 in the *Wind_parks_EYield* scenario. Differences in total potential to Figure 1 are due to the cut-off at 1 £/kWh. Wind speed data is from the Met Office 2018[54].

Figure 5 illustrates the normalized marginal LCOEs – i.e. based on the additional costs and potential for one scenicness class – and cumulative generation potentials for progressively-increasing upper bounds of scenicness. It shows a strong linear correlation between scenicness and the marginal LCOEs and the cumulative generation potentials respectively. For the scenarios *Wind_parks_EYield* and *Turbine_no_conn,* the implications of progressively excluding the most scenic areas for costs and potentials are revealed. For example, removing the 10% most scenic areas in Great Britain implies around 17% less potential in both scenarios, whereas the marginal LCOEs increase by 26% and 8% in Wind_parks_*EYield* and *Turbine_no_conn* respectively. This cost increase for exploiting the same high-quality wind locations needs to be weighed against the avoided, external costs to affected communities, as returned to in the discussion.

As well as the example of Scout Moor above, the largest British onshore wind farms are located within the 10% most scenic areas, namely Whitelee with 539 MW and maximum scenicness values nearby of 6.4, Crystal Rig 2 & 2a (138 MW and 7.3) and Arecleoch (120 MW and 7.4). All of the photos from which these scenicness values derive were taken before the erection of the respective wind farms, meaning they would not have been built if excluding the 10% most scenic areas in the planning process. This may seem like a contradiction of the findings above relating planning applications to scenicness, but really only shows that more rejected applications are required for each positive one in a given location.

The significant difference in cost between the *Wind_parks_EYield* and *Turbine_no_conn* scenarios again emphasizes the importance of considering the connection costs for remote and scenic locations: more scenic sites tend to be natural areas[24], with features such as mountains and valleys[24], which therefore results in larger distances from and higher connection costs to the nearest transformer stations. The inverse also applies: sites with lower scenicness values are neither associated with a particularly good wind resource, nor are they located far from the nearest transformer, as they tend to be in built-up urban, surburban and industrial areas[24,41]. Overall, then, the network costs make the overall costs higher, but all other things being equal the LCOEs are lower in more remote locations.

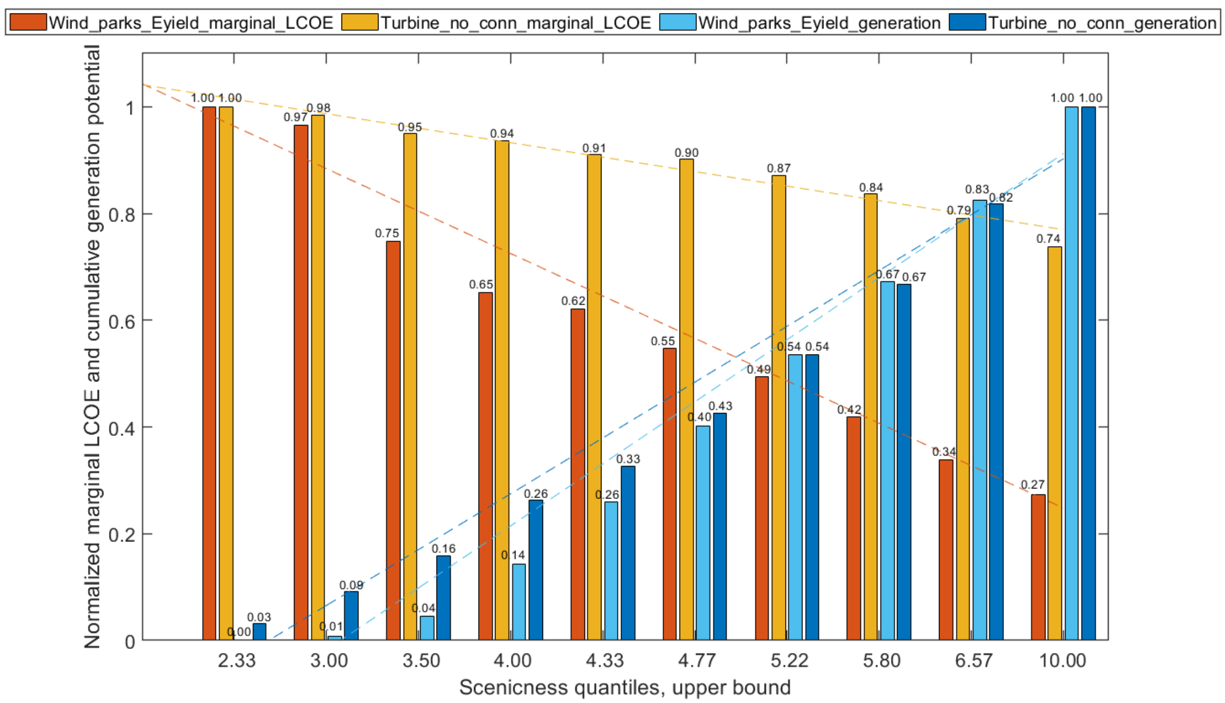

Figure 5 | Normalized marginal LCOEs and cumulative generation potential for scenicness quantiles. The x-axis gives the upper bound of each quantile. Linear regressions from top to bottom: y=-0,037x+1.077, R^2=0.93; y=-0.100x+1.099, R^2=0.79; y=0.141x-0.266, R^2=0.92; y=0.155x-0.376, R^2=0.89

Discussion

Our analysis represents a quantitative framework to assess the trade-off between cost-efficiency for onshore wind and the protection of beautiful landscapes, a key element of public acceptance. Approximating public acceptance by visual impact, operationalized through the scenicness dataset, is an approach which has some inevitable shortcomings. First and foremost is the lack of economic value for the public acceptance, which would be required for an exhaustive analysis of this trade-off. Combining insights relating to actually-paid compensations with stated (from surveys) and revealed (from property prices) preferences enables aggregated acceptance costs to be estimated.[37] But monetary valuations of public acceptance are notoriously uncertain as well as person- and location-specific. At the very least, spatially-disaggregated data relating to these preferences in Britain would be required in order to draw up a complete balance sheet. This data needs to take into account the impact on communities living in the vicinity of new or existing wind farms, but also to consider the economic value of beautiful landscapes. This would involve considering the number or frequency of 'sightings' as well as the actual value (per sighting) as inferred by scenicness. Similarly, previous research has shown that scenic environments are not only environments that people prefer but are also linked to increased health and happiness[24,40]. Improving health and wellbeing is also an important policy goal for decision-makers, and a failure to achieve this goal can have high economic costs, further complicating the trade-off between cost-efficiency of onshore wind and landscape protection.

We adopt the perspective of a neutral investor and do not distinguish between large(r) utility-scale wind farms and small(er) community scale-ones. In practice, however, the difference is important, both in terms of the economic criteria applied to the project and its local acceptability. There is abundant evidence in the literature that local community involvement in onshore wind (and other community energy) can increase the acceptance and thereby ameliorate some of the otherwise negative aspects that may be associated with larger utility-scale projects.[38,39] Furthermore, the focus in the acceptance literature has recently shifted away from aesthetic/landscape considerations towards more holistic concepts of empathy, place and identity[64,65]. Related to this point is the question of land ownership and use, recreational or otherwise. The owners of the land not only have ultimate decision-making authority in the context of onshore wind developments, they also stand to directly benefit from the investment whilst also potentially suffering adverse landscape impact effects (costs).

The use of the scenicness database as an indicator of the scenic beauty of the area also relies a number of assumptions. Crucially, the ratings are of photographs rather than direct ratings of the locations themselves. The ratings of photographs are likely to be influenced by temporary features of a scene, such as the weather, as well as the skill and mood of the photographer, which add noise to the dataset. Images may not be representative in certain locations[55], in particular when one photograph is used to evaluate the appeal of $1km^2$, partly because photographers will be more likely to take photographs in some locations than in others. Similarly, the prominence of large objects in a scene may be judged differently from a photograph than when viewing the scene in situ, an issue that can be exacerbated by the chosen focal length[59]. Nevertheless, previous work has demonstrated that ratings of photographs do tend to correlate well with ratings given whilst standing in the location itself[55,57]. The *Scenic-Or-Not* dataset also benefits from the fact that it draws on a moderated set of photographs from the *Geograph* project, which has an explicit aim to collect geographically representative photographs, such that the photographs are more standardised and focused on landscapes than a random sample of geotagged photographs would be.

A further concern relates to how users of *Scenic-Or-Not* may have interpreted the core construct of 'scenic'. For example, would different results have been obtained if *Scenic-Or-Not* users had been asked to rate how 'beautiful' an image is? Earlier analyses of the *Scenic-Or-Not* data do however provide some insight into the characteristics of an image that influence the 'scenic' measure. These results make it clear that measurements of scenicness are not simply the same as measurements of greenspace[40], and indeed that man-made structures such as viaducts, castles and lighthouses can in some circumstances boost the aesthetics of a scene.[41]

To extend our approach to other countries, a starting point could be to identify similarities and differences between acceptance and planning procedures elsewhere.[42] Either a set of images of the environment taken at eye-level is needed, or a relationship between scenicness and land use categories.[43] For the former, scenic ratings of the images could then be crowdsourced like for *Scenic-Or-Not* or estimated using computer vision approaches.[41] Further crowdsourced ratings or deep learning estimates would make it possible to increase data granularity above one photograph per 1 km^2. Ratings for further photographs would also help ensure that views in different directions were taken into account for each area. In addition to scenic ratings, approaches drawing on diverse topographical and cultural landscape metrics were able to explain 64% of the scenicness variation across Germany.[56] This framework could also be enhanced to consider the size and type of turbines installed, introduce a setback distance that can strongly increase acceptance[9,44] or account for the experience that local communities already have with wind energy.[10,11,12] Future work should also assess the impact of electricity network lines and/or transport infrastructure passing through scenic areas as well as measures such as burial of these lines to mitigate their landscape impact. The approach could also include estimates of the potential impact of changes to landscape aesthetics on happiness and health, building on the modelling reported by Seresinhe et al.[24,40], to help policymakers understand the range of trade-offs at play.

Table 3 | Sensitivity analyses: logistic regression results for project planning outcome, showing two models for wind energy and one for solar energy

	Model 1 Wind energy probit	Model 2 Wind energy logit$^{\$}$	Model 3 Solar energy logit
Scenicness value	-0.148***	-0.254***	-0.030
	(0.028)	(0.206)	(0.054)
Number of turbines	0.121***	0.206***	
	(0.014)	(0.025)	
Capacity	-0.040***	-0.067***	-0.013
	(0.005)	(0.009)	(0.008)
log distance to the closest National Park	0.093***	0.160***	0.101*
	(0.033)	(0.058)	(0.060)
log distance to the closest airport	-0.001	-0.016	0.209**
	(0.068)	(0.113)	(0.090)
log distance to the closest Special	-0.022	-0.033	-0.030
Protection Area (SPA)	(0.026)	(0.044)	(0.096)
log distance to the closest Special	-0.072**	-0.131*	-0.282***
Areas of Conservation (SAC)	(0.036)	(0.061)	(0.081)
log distance to the closest Ramsar areas	0.015	0.031	0.026
	(0.035)	(0.060)	(0.082)
Year fixed effect	yes	yes	yes
Constant	0.240	0.516	0.612
	(0.856)	(1.378)	(0.682)
Number of observations	1,324	1,169	1,558
AIC	1425.84	1402.43	1422.88

Log likelihood	-688.92	-677.22	-697.44

Notes: discrete dichotomous variable taking a value of 1 if the application decision is positive, otherwise 0; ***, **, * indicate that estimates are significantly different from zero at the 0.01, 0.05 and 0.10 levels, respectively; standard errors are in parentheses. Coefficients are reported without any transformation, in contrast to Table 1, where log-odds coefficients are transformed to odds ratios for ease of interpretation. *AIC is Akaike's[29] information criterion. $# votes>4 (10% percentile).*

Finally, it is important to stress that wind energy should be considered in the context of other alternatives and their like-for-like impacts across all categories.[45] This means assessing the relative impact for one unit of energy of wind turbines alongside alternatives such as coal, gas and waste power plants. The static viewpoint adopted here should also be extended to embrace the dynamic processes of energy system transition and changing acceptance, but this is partly hindered by a lack of longitudinal studies.[46,47] Ultimately, research on the social acceptance of wind energy is highly heterogeneous with some contradictory findings[11], which encourages widening the scope of this research to consider additional perspectives.[48] To relieve the tension between ambitious energy system transformations and democratic social process[49], compromises will have to be made at all levels.

Conclusions

To conclude, we return to the research questions posed at the outset. Firstly, the outcome of planning applications for onshore wind are strongly correlated with scenicness: an application with 1% higher scenicness value has 6% lower probability to be evaluated positively. Secondly, we found a strong link between locations with an economical wind resource and high scenicness. The better wind resource in more remote locations means that the total generation costs more than double, however, if network connection costs are considered. Thirdly, compared to the technical potential of onshore wind of 1700 TWh at total costs of £280 billion, removing the 10% most scenic areas implies about 18% lower potential and 8-26% higher costs. All of these findings mean that trade-offs will be inevitable if sustainable energy policies are to reflect public concerns and offer the maximum possible economic, social and wellbeing benefits.

Methods

1. Regression of planning outcomes and scenicness

In addition to the scenicness data, we also employ the Renewable Energy Planning Database (REPD), which includes the date of the application, operator, information on the site (name, address and coordinates), technology concerned, project capacity, the number of turbines (for the wind energy projects), and the outcome of the application (granted or rejected). For onshore wind energy, 568 project applications have been rejected and 756 have been granted for the time period 2001-2017, so the mean success rate is about 0.6 (Table 1). This data is spatially connected to the scenicness data, whereby the mean scenicness and distance of the nearest wind polygons from the geometric centre of the wind park (planned or existing) is computed. For the 1324 project applications considered, the scenicness values are in the range from 1 to 8.67 with a mean value of about 4.15. The latitude and longitude of the planned renewable plants from the REPD are compared with the centre of the 1km raster of the scenicness dataset. For existing wind parks, the centroid of the park area is employed. There are only a few high scenicness values (99% percentile is 7.80), see also Figure 1*a*. It is slightly higher for rejected applications. Each scenicness value is associated with number of votes. The mean number of the actual votes per picture is about 6.76 (Figure 1*b*). The sample also includes other relevant variables that have been selected following findings in Roddis et al.[31] and Harper et al.[30] These variables are computed from protected sites data extracted from the Joint Nature Conservation Committee website[50] and the National Parks data from the Office for National Statistics.[51] To account for non-linear effects related to distance, all variables describing the geographical distance are transformed using a natural logarithm before being included in the statistical models.

Table 1 shows summary statistics for the final sample of planning applications used for estimation. Given the uncertainty surrounding the scenicness values (the average rating of photos) when the number of votes is low, in the empirical analysis we estimate models when we remove the 10% of photos with the lowest number of votes as a robustness check. This does not affect the interpretation of the results, as explained in more detail below.

In our analysis, we assume a standard specification for the planning outcome for a project application i at year t:

$$\Pr\left(\mathrm{D}_{i,t} = 1 \mid \mathrm{S}, \mathbf{X};\ \alpha, \beta, \boldsymbol{\delta}, \boldsymbol{\gamma}\right) = \mathrm{F}\left(\alpha + \beta\, S_{i,t} + \boldsymbol{\delta}' \boldsymbol{X}_{\boldsymbol{i},\boldsymbol{t}} + \boldsymbol{\gamma}_{\boldsymbol{t}}\right) \quad (1)$$

where $D_{i,t}$ denotes the discrete dichotomous variable taking a value of 1 if the application decision is positive, otherwise 0; α is a constant term and γ is the year fixed effect; $S_{i,t}$ is the scenicness value; and $\boldsymbol{X}_{\boldsymbol{i},\boldsymbol{t}}$ denotes controls for project characteristics such as technical and geographical attributes. The coefficients (α, β, $\boldsymbol{\delta}$ and $\boldsymbol{\gamma}$) are estimated using maximum likelihood assuming that the error term is identically and independently Extreme Value Type I distributed (i.i.d. EV I), so $F(z) = e^z/(1 + e^z)$ is the cumulative logistic distribution. A particular advantage of the logit model over the linear probability models is that it has a choice theoretic interpretation.[52] We are particularly interested in the value of β, as if the scenicness is not related to the application decision then $\beta = 0$, whereas $\beta < 0$ if the scenicness value negatively impacts the planning outcome.

A series of logit models are estimated, the first with only the main variable of interest (the scenicness value) and the following models including additional variables, which have been selected following the relevant literature[30,31], see Table 2 in the main text. Finally, we also include a year fixed effect to account for possible year-specific structural trends such as business cycles, inflation and political environment.

We have performed a number of sensitivity analyses in Table *3*. First we assume that the error term is i.i.d. normally distributed. In this case the inverse standard normal distribution of the probability is modelled as a linear combination of the predictors. The estimation results are reported in Table *3* Model 1. The estimated coefficient associated with the scenicness value is negative and significant. Model 2 in Table *3* reports the results of a logit model (the error term is i.i.d. EV I) estimated on a subsample when the number of votes is larger than 4 (10% percentile). The coefficient associated with the scenicness value is again negative and significant. We have also estimated models when the number of votes is larger than 5 (25% quartile) and 6 (median) and the coefficient remains unchanged. Finally, we also conduct an additional sensitivity test, which entails replicating our baseline estimate by using ground-mounted solar panel project planning outcomes as the dependent variable. We observe 1,558 solar energy project applications, where 283 project applications were rejected and 1,275 were granted during the time period 2011-2017. We expect this effect to be zero because the impact of ground-mounted solar panels on landscape aesthetics is less pronounced. The estimated coefficient associated with the scenicness value is indeed small and statistically insignificant (Table *3* Model 3).

2. Feasible wind potentials and acceptance definition

The general approach to determining feasible areas and technical generation potentials for onshore wind in Great Britain follows the one in McKenna et al.[34] The suitable areas and offset distances for onshore wind turbines are taken from the cited source. Existing wind turbines and sites are removed based on OSM data[53] with the Overpass Turbo tool. The wind data employed consists of monthly mean wind speeds for the years 2001-2006 at 5 km^2 spatial resolution.[54] These years have an average capacity factor for onshore wind of 24%, which broadly correspond to the long-term average in the UK.[33] The scenicness data is linked to the wind polygons through the 1km^2 and the polygon's geometric centre. In addition to the feasible areas and mean wind conditions, the determination of the technical potential is also based on a turbine database, containing capacities, power curves and costs. The most suitable turbine type is selected for each wind polygon based on LCOE or energy yield, whereby connection costs to the nearest transformers are also considered in three scenarios, as outlined in the main text.

The term public acceptance is defined in this paper based on Wüstenhagen et al.'s[60] framework, with acceptance subject, object and context according to Lucke[61], and by the definition of acceptance based on Schweizer-Ries[62]. Lucke stresses that the subject (e.g. person, institution, company) may assume different roles, whilst the object of acceptance (e.g. policy, technology, infrastructure) and its context (e.g. national, local) may vary. Schweizer-Ries defines the term acceptance in the context of renewable energies by an attitudinal and an action-level, so the definition differentiates between four levels of (non)-acceptance: passive acceptance, called "approval", and active acceptance, called "support", passive non-acceptance, called "rejection", and active non-acceptance, called "resistance" (cf. also Rau et al.[63]). Arguably this quadripartite concept is overly simplistic as it overlooks some of the nuanced dynamics, positions and actions relating to public acceptance. But the concept does allow a working definition of (public) acceptance to be formulated and applied.

Hence, in this paper we employ scenicness data based on crowd-sourced images and ratings in order to represent the public's (subjects) appreciation of the landscape. The focus in this study is on onshore wind energy (object) in Great Britain (context). In terms of the dimensions explored, we can only claim to consider community acceptance in this study, as we do not have representative sample of the population (such as in the cited YouGov survey[3]) to derive insights about their preferences. Similarly, whilst we touch on market acceptance, we only do this indirectly in the sense that local opposition to proposed wind farms might result in them not being built. But this is a purely local phenomenon (NIMBY), i.e. the local opposition in one location does not necessarily (or only marginally) affect the uptake of onshore wind energy across the UK as a whole. For these reasons, we constrain our definition of acceptance to community acceptance, whilst recognising this small fraction of market acceptance that we capture.

3. Retrieval of transformer locations

After the determination of the technical potential, the wind turbines have to be connected to the National Grid. Typically, larger wind plants are connected to transformers with a voltage level of 132 kV (https://wiki.openstreetmap.org/wiki/Power_networks/Great_Britain). The transformers are determined with the following query in OSM:

```
[timeout:900];
area["ISO3166-1"="GB"]->.a;
(
 relation["power"="substation"]["voltage"~".*132000.*"](area.a);
 way["power"="substation"]["voltage"~".*132000.*"](area.a);
 relation["power"="sub_station"]["voltage"~".*132000.*"](area.a);
 way["power"="sub_station"]["voltage"~".*132000.*"](area.a);
 relation["power"="station"]["voltage"~".*132000.*"](area.a);
 way["power"="station"]["voltage"~".*132000.*"](area.a);
);
out qt;>;out qt;
```

Smaller wind plants are generally connected to 33 kV or 13 kV. The latter is the final-level distribution voltage (https://wiki.openstreetmap.org/wiki/Power_networks/Great_Britain). These transformers can be retrieved by replacing 132000 with 33000 or 11000 in the query above. The voltage 13 kV is not used as a tag in OSM, therefore, we assume that the 11 kV transformers are equivalent to the 13 kV transformers. This voltage level is closest to the 13 kV. The next voltage levels in OSM would be 6.6 kV and 25 kV.

This procedure resulted in 964 transformers at 132 kV, 1115 at 33 kV and 673 at 11 kV (cf. left part of Figure 2). For the northern part of Great Britain (e.g. the Shetland Islands), only 19 transformers without voltage classification could be retrieved. Therefore, these 19 transformers are not used in the following analyses. Many transformers include connection points for more than one voltage level. In these cases, the transformers are plotted on top of each other in Figure 2 and only one transformer is visible for the relevant location.

4. Determination of network connection costs

As a cost estimation for connecting the wind plant with transformers, linearized functions were derived from the National Grid's cost estimator (https://www.nationalgridet.com/get-connected/cost-estimator). The National Grid is the owner of the electricity transmission network in England and Wales. The costs of connection, costs for site-specific maintenance as well as transmission running costs depend on the voltage level of the transformer, generation capacity of the wind plant and the area classification. The classification of areas distinguishes between urban and rural. The costs include fixed costs C_F and variable costs C_V that depend on the length of the connection line. The fixed and variable costs for the connection to the different voltage levels are given in Table 1 (Extended Data). According to the National Grid, for connections up to 50 MW, 13 kV is the most appropriate voltage, and the same is true for 135 MW and 33 kV as well as 300 MW and 132 kV (https://www.nationalgridet.com/get-connected/cost-estimator). In Table 1 (Extended Data), the interval for 132 kV only reaches 240 MW, since the National Grid cost estimator only indicates costs up to this value. None of our wind farms has a larger capacity.

5. Area classification for cost estimation

The classification of areas into urban or rural is necessary for the cost estimation. The official classifications in England and Wales (https://geoportal.statistics.gov.uk/datasets/276d973d30134c339eaecfc3c49770b3) as well as Scotland (https://www2.gov.scot/Publications/2018/03/6040/downloads) are used for this purpose. As can be seen in the right panel of Figure 5, there are significantly more urban areas (brown shapes) in England than in Scotland and Wales. We use two different definitions for wind farms in two scenarios, which are explained in Sections 6 and 7 respectively.

6. Separate consideration of wind polygons

In the first case, wind farms are represented by the wind polygons (scenario *Turbine_no_conn*). Here, the centroids of the wind polygons are used as an estimate for the length of the connection lines (*Turbine_conn*).

Figure 1 (Extended Data) shows the connections with the nearest three transformers of the different voltage levels for an example wind polygon. In the next step, the connections are intersected with the urban areas. The red part of the black connection lines in Figure 1 (Extended Data) shows the proportion of connections leading through urban areas. The length of the connections through rural and urban areas were calculated for all wind polygons.

Since the maximum capacity of a wind farm corresponds to the most economical option due to economies of scale, this capacity is assumed for each wind farm when calculating the connection costs. The selection of the turbine type is done (according to McKenna et al.[34]) simultaneously with the determination of the connections to the transformers. Previously, the wind turbines were only selected based on the lowest LCOE (i.e. for scenarios *Turbine_no_conn* and *Turbine_conn*). Now the calculations could result in a wind turbine with a higher LCOE. When considered simultaneously with the connection costs, this might lead to lower overall LCOEs due to a higher energy yield.

7. Cluster of wind polygons into larger wind farms

In a second case, the individual wind polygons are combined to form larger wind farms. For this purpose, buffer zones with a radius of 1 km are formed around the centroids of the individual wind polygons. The 1 km is chosen to represent the minimum distance between turbines (eight times the rotor diameter). The wind polygons, where these buffer zones overlap, can be combined in a next step to form a contiguous wind park. To ensure that this does not result in a wind farm that is far too large, the maximum capacity of the wind farms is limited to 240 MW (cf. maximum capacity in Table 1, Extended Data). This results in 29,060 wind farms with capacities between 1.9 MW and 240.0 MW (mean value = 231.2 MW). Figure 2 (Extended Data) shows resulting wind parks for a specific area in

Great Britain. However, these capacities only represent upper bounds, since turbines with a lower capacity density could also be selected in the algorithm.

In contrast to the calculation with separate wind polygons in section 6, the connection costs to the transformers are not simultaneously included with the costs for the individual wind turbines. Instead, for each wind polygon in the simulation, the wind turbine types are selected first, and then the connection costs are added to determine the overall LCOE. The distance of the centroid of the wind farm (cf. stars in Figure 2, Extended Data) to the transformers is used to estimate the connection costs. Since the connection costs are added afterwards, the wind turbines are selected in the first step in two cases with different criteria: 1) minimum LCOE (*Wind_parks_LCOE*), 2) maximum energy yield (*Wind_parks_EYield*).

Data Availability Statement

The data employed in this paper can be accessed on Figshare at https://figshare.com/articles/dataset/Quantifying_the_trade-off_between_cost-efficiency_and_public_acceptance_for_onshore_wind/12998693. The suggested citation is as follows: McKenna, Russell; Weinand, Jann; Mulalic, Ismir; Petrovic, Stefan; Mainzer, Kai; Preis, Tobias; et al. (2020): Quantifying the trade-off between cost-efficiency and public acceptance for onshore wind. figshare. Dataset. https://doi.org/10.6084/m9.figshare.12998693.v1

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Author contributions

RM conceived and designed the research. RM, JW, IM, SP, and KM carried out the analysis. RM, JW, IM, SP, KM, TP and HSM contributed to analysis design and interpretation. TP and HSM provided the scenicness data. RM led the preparation and revision of the manuscript. RM, JW, IM, SP, KM, TP and HSM drafted text and edited the manuscript. RM provided institutional and material support for the research.

Additional information

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Competing interests

The authors declare no competing interests.

Supplementary Information

for

Scenicness assessment of onshore wind sites with geotagged photographs and impacts on approval and cost-efficiency

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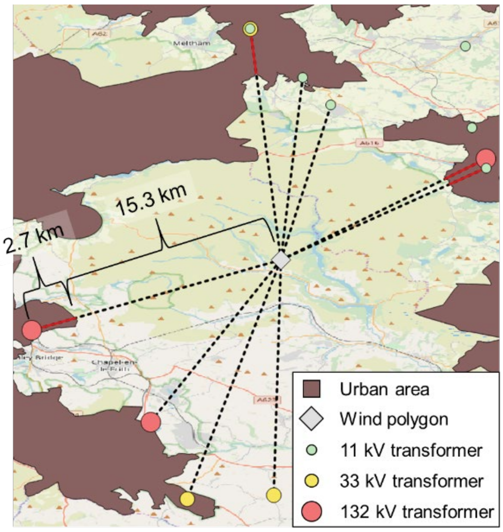
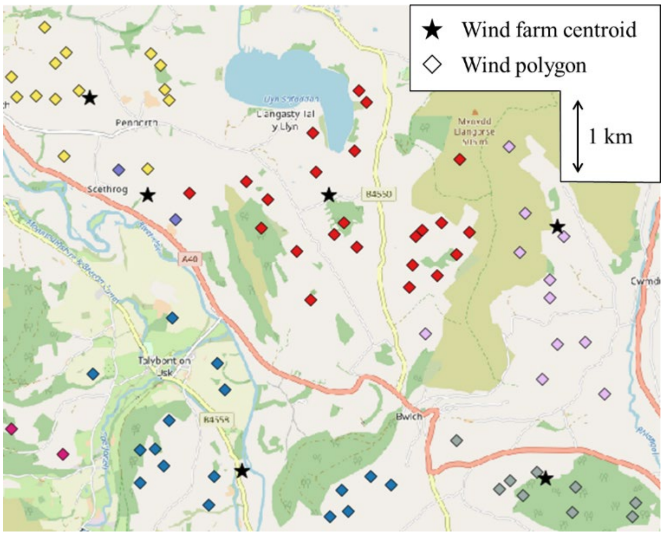
Supplementary Table 1 | Costs for connection of a wind farm to a transformer, depending on voltage level, generation capacity and area classification (https://www.nationalgridet.com/get-connected/cost-estimator).

Voltage level [kV]	Generation capacity interval [MW]	Area classi-fication	Connection		Maintenance		Transmission running	
			C_F [M£]	C_V [M£/km]	C_F [k£]	C_V [k£/km]	C_F [k£]	C_V [k£/km]
13	[0; 50]	rural	2.3	1.1	14.1	6.8	49.9	19.2
		urban	2.9	1.4	17.6	8.4	50.3	24.1
33	(50; 90]	rural	2.0	1.1	12.0	6.8	34.2	19.2
		urban	2.4	1.4	15.0	8.4	42.7	24.1
	(90; 120]	rural	4.7	1.1	28.8	6.8	82.0	19.2
		urban	5.9	1.4	36.0	8.4	102.5	24.1
	(120; 135]	rural	5.7	1.1	34.6	6.8	98.8	19.2
		urban	7.1	1.4	43.3	8.4	123.4	24.1
132	(135; 240]	rural	5.3	1.9	32.6	11.5	92.9	32.7
		urban	6.7	2.3	40.7	14.3	116.1	40.9



Supplementary Figure 1 | Possible connection lines of one wind farm to the nearest three transformers of each voltage level. The red part of the lines leads through urban areas. Data is from OSM[53] and ONS[66], as detailed in the article text.



Supplementary Figure 2 | Combination of wind polygons to wind farms for a specific area in Great Britain. The colours of the wind polygons indicate different wind parks. Data is from OSM[53] and ONS[66], as detailed in the article text.