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## Improving renewable energy resource assessments by quantifying landscape beauty

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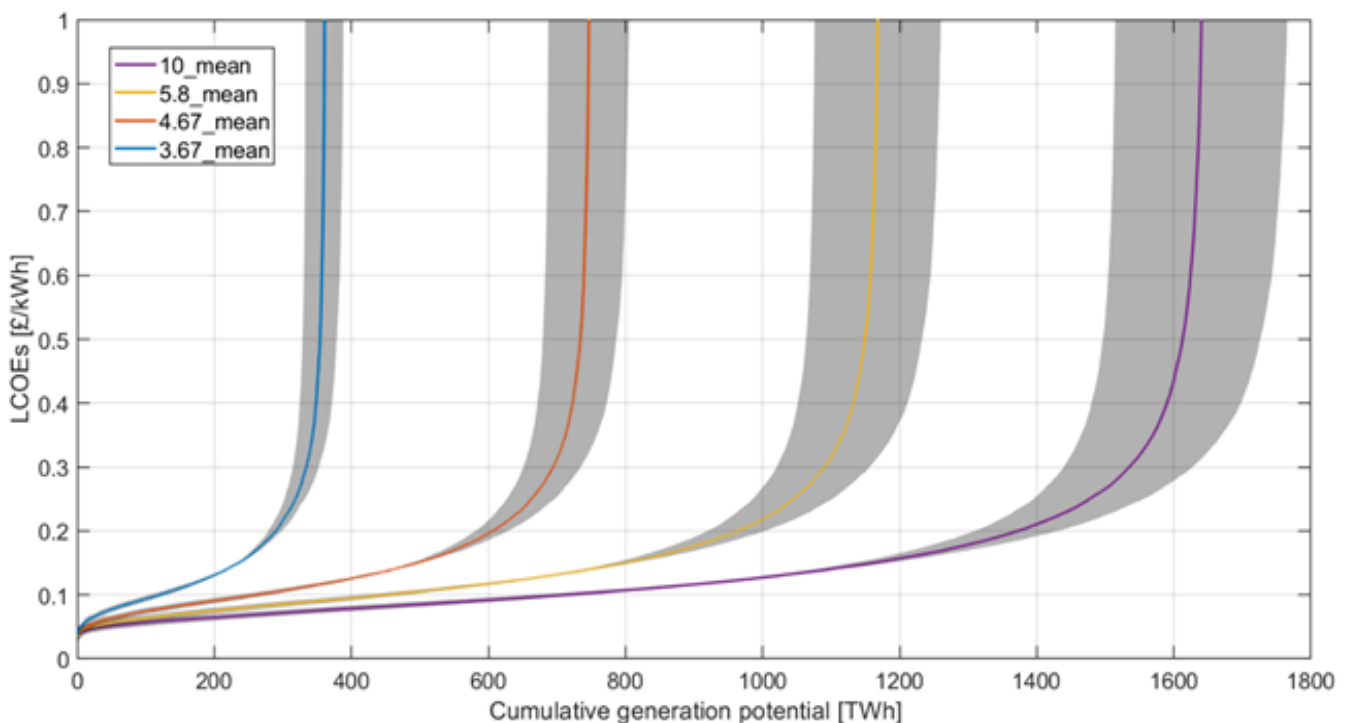
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# Improving renewable energy resource assessments by quantifying landscape beauty

By Russell McKenna, Jann Michael Weinand, Ismir Mulalić, Stefan Petrović, Kai Mainzer, Tobias Preis, Helen Susannah Moat

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A cost-efficient and sustainable energy transition requires reliable information about the distribution of renewable energy resources. Here we draw on over 1.5 million scenicness ratings of around 200,000 geotagged photographs from Scenic-Or-Not to quantify the aesthetic value of the landscapes in which onshore wind energy installations could be situated in Great Britain. An analysis of planning applications provides quantitative evidence that onshore wind projects are more likely to be rejected when proposed in more scenic areas. Exploiting further open data sources including OpenStreetMap, we build on these findings to generate new estimates of the feasible potential and costs for onshore wind in Great Britain, which we find to be around 1700 TWh and £280 billion respectively. We also uncover a strong spatial correlation between scenicness and the quality of the wind resource, implying inevitable trade-offs between cost-efficiency and public acceptance.

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## Abstract

A cost-efficient and sustainable energy transition requires reliable information about the distribution of renewable energy resources. Here we draw on over 1.5 million scenicness ratings of around 200,000 geotagged photographs from *Scenic-Or-Not* to quantify the aesthetic value of the landscapes in which onshore wind energy installations could be situated in Great Britain. An analysis of planning applications provides quantitative evidence that onshore wind projects are more likely to be rejected when proposed in more scenic areas. Exploiting further open data sources including OpenStreetMap, we build on these findings to generate new estimates of the feasible potential and costs for onshore wind in Great Britain, which we find to be around 1700 TWh and £280 billion respectively. We also uncover a strong spatial correlation between scenicness and the quality of the wind resource, implying inevitable trade-offs between cost-efficiency and public acceptance.

In the context of many countries' transitions to sustainable energy systems, detailed resource assessments for renewable energy technologies are required. These data are often employed by researchers and policymakers as input to large energy system models with which to analyze future energy scenarios.<sup>1,2</sup> Resource assessment methods have recently been improved by developing open source methods<sup>3</sup>, employing more accurate data<sup>4,5</sup> and considering non-technical and especially social constraints<sup>6,7,8</sup>, including the visual impact of renewable technologies on the landscape.<sup>9,10,11,12</sup> But none of these previous studies has explored the implications of public attitudes within a quantitative framework at the national scale.

In the British context adopted for this research, there has been intense discussion around the future role of onshore wind energy. From 2015 until very recently, onshore wind was no longer eligible for subsidies in the Contracts for Differences<sup>1</sup> auctions.<sup>13</sup> Yet onshore wind has very high approval ratings, as highlighted by some recent surveys. Overall support for renewable energy reached its highest ever level, at 85% in 2018,

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<sup>1</sup> Effectively a market-oriented price-based subsidy.

increasing from 79% in 2017.<sup>14</sup> A YouGov<sup>15</sup> survey ranked onshore wind as the cheapest perceived technology out of all options, as well as finding general support for onshore wind development as a technology, with *tend to* and *strongly support* together representing around 70% of responses.

Despite this general approval, onshore wind can encounter local opposition from stakeholders, especially if they are not directly engaged in the planning and investment processes.<sup>9,10, 16,17</sup> Visual impact is one of the central arguments that local residents make against onshore wind installations<sup>18,19,20</sup>, although concern is reduced when people live further away from wind turbines<sup>20,21,22,23</sup> and in contexts where the affected people have previous experience with wind energy.<sup>21,24,25,26</sup> Detrimental effects on the visual landscape are not only a concern for public acceptance; more scenic environments are typically associated with greater health and happiness, even when potential confounds such as greenspace or income levels are considered<sup>27,28</sup>, suggesting that such planning decisions could have consequences for human wellbeing too.

A related discussion addresses the whole system costs of renewable energies. A common benchmark for power-generating technologies is the Levelized Cost of Electricity (LCOE). Contrary to conventional power generators, non-dispatchable renewables require additional investments in order to integrate them into the energy system. This has led to the concept of system LCOEs, which include the grid costs to connect or extend the electricity network, the profiling costs due to the “residual” power system having to modulate its output, and balancing costs due to the inaccuracy in forecasts and needs for the system to provide short-term flexibility.<sup>29,30,31</sup> Accounting for all three of these requires power and energy system models at a high enough level of detail<sup>1,2,32</sup>, whereby computational complexity often dictates a focus on one or two of these fractions.

Against this background, this paper addresses the following research questions:

1. **How can the accuracy** of renewable energy potential assessments be increased by employing open geospatial data?
2. **What impact do the grid connection costs** have on onshore wind generation costs?
3. **Beauty of the landscape, i.e. scenicness:**
  - Is scenicness already implicitly considered in planning practice for onshore wind?
  - How, if at all, is scenicness related to the resource potential for onshore wind?
  - What is the impact of scenicness on the costs and potentials of onshore wind?

## **Advantages of combining geospatial data sources**

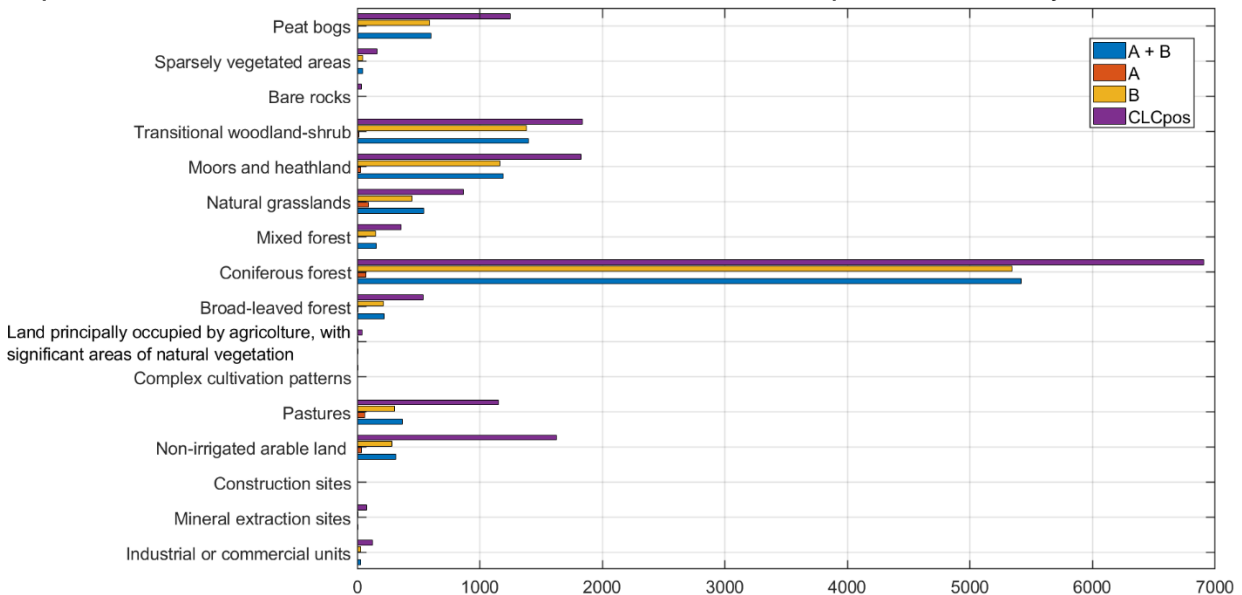
Here we explore the impact of employing OpenStreetMap<sup>33</sup> data alongside CORINE Land Cover<sup>34</sup> (CLC) data to identify suitable areas for onshore wind. Whilst the former has a higher spatial resolution it suffers from incomplete coverage, especially in rural areas (19 land use categories plus roads, railways, water/water bodies). In contrast, CLC has complete coverage for the whole of Europe, but at a resolution of only 100 m<sup>2</sup> (44 categories). For example, OSM has more details in urban areas, such as forest, park, residential, industrial, farm, cemeteries, allotments, meadows, commercial. On the other hand, the corresponding CLC dataset only differentiates continuous and discontinuous urban fabric, industrial or commercial units, road and rail networks and associated land, green urban areas, sport and leisure facilities.

Both datasets are employed here alongside the assumed suitable areas and offset distances shown in McKenna et al.<sup>35</sup> To assess their combined efficacy we first compute the positive (suitable for onshore wind) and negative (unsuitable for onshore wind) areas, which we refer to as  $OSM_{pos}$ ,  $OSM_{neg}$ ,  $CLC_{pos}$  and  $CLC_{neg}$  respectively. Given that the higher resolution of OSM can offer two types of enhancements, by both including and removing additional areas respectively, we then perform two steps to exploit the advantages of using two datasets. Firstly we calculate a new area  $A = OSM_{pos} - CLC_{pos}$ , to account for the incorrectly excluded areas according to CLC. Secondly, we calculate a new area  $B = CLC_{pos} - OSM_{neg}$ , in order to account for (small) negative areas within the positive CLC areas. Finally we take the union of A and B to arrive at a revised total geographical potential.

**Table 1 | Suitable areas from OSM and CLC for onshore wind in Scotland**

Area name	CLC	$CLC_{pos}$	$CLC_{neg}$	OSM	$OSM_{pos}$	$OSM_{neg}$	A	B	A + B
Area (km <sup>2</sup> )	78856	71175	7681	20400	10356	10044	366	49048	49542

In Table 1 and Figure 1, we illustrate this process using the example of Scotland, due to the large available area, high wind speeds and scenicness values in that location. In this case, the coverage of OSM is around 25% or 17794 km<sup>2</sup> of the total area of 78964 km<sup>2</sup>. The figure shows that the OSM data implies a reduction in the total available area for onshore wind from  $CLC_{pos}$  by about 21633 km<sup>2</sup>, based on summing ( $CLC_{pos} - (A+B)$ ) (Table 1 and Figure 1). Of this, about 54% is in coniferous forest, 14% is in transitional woodland shrub, 12% in moors and heathland, 6% peat bogs and 5% natural grasslands, as well as other small contributions. For the whole of Scotland, the use of OSM reduces the positive area from 71000 to 49000 km<sup>2</sup>, i.e. reduces the potential area by about 31%.

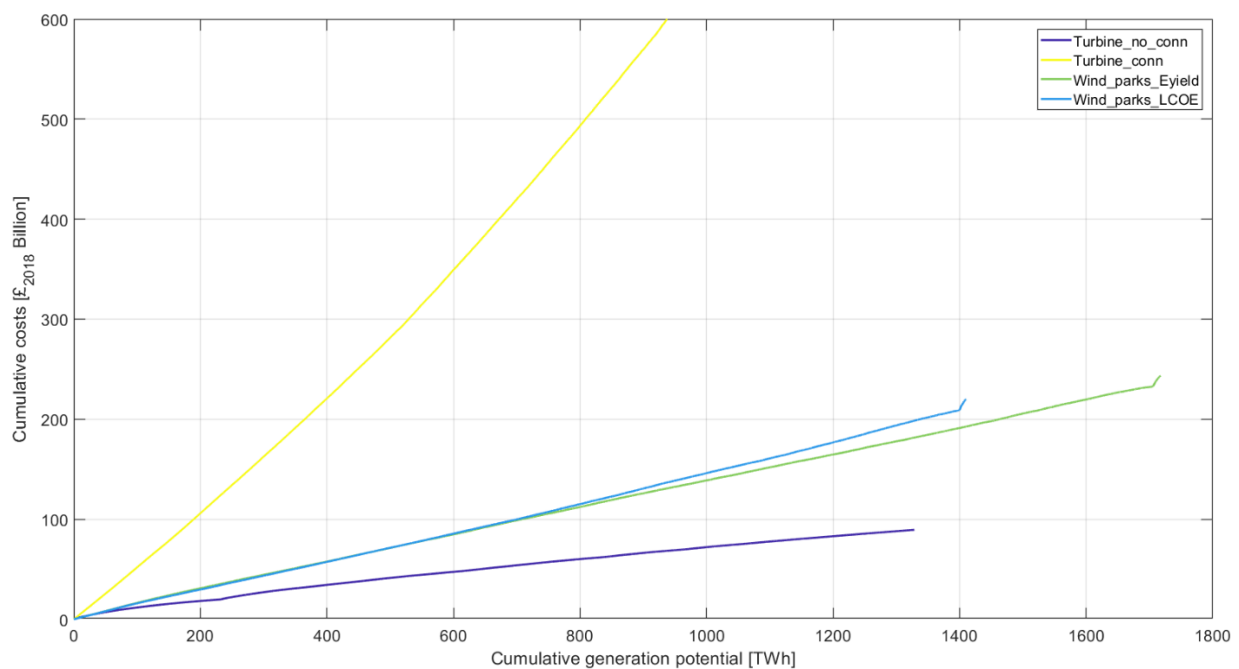


**Figure 1 | Reduction in potential areas for Scotland based on CLC and OSM, with areas < 1 km<sup>2</sup> not shown. The area  $CLC_{pos}$  is reduced to A and increased by B to yield the net available area for onshore wind.**

## Impacts of grid connection costs on onshore wind

In order to explore the implications of scenicness and wind turbine clustering on the costs and potentials of onshore wind in Great Britain, the following four scenarios are defined (for details see methods section):

- Individual wind polygons<sup>2</sup> without network connections, *Turbine\_no\_conn*
- Individual wind polygons with individual network connections to the nearest transformer, *Turbine\_conn*
- Wind polygons clustered into wind parks with network connections to nearest transformer, based on the maximisation of the energy yield, *Wind\_parks\_Eyield* – employed here as the “reference” scenario as considered most realistic
- Wind polygons clustered into wind parks with network connections to nearest transformer, based on the minimisation of the LCOEs, *Wind\_parks\_LCOE*



**Figure 2 | Cumulative costs and potentials of onshore wind in Great Britain, with and without network connections costs in four analysed scenarios. We also depict Great Britain’s national electricity demand<sup>36</sup> and electricity generation from onshore wind in 2018<sup>37</sup>. The extreme value for Turbine\_conn is about 1610 TWh and £ 1470 Billion.**

To analyse the impact of grid connection costs, we first determine and economically assess potential locations and capacities for onshore wind, and then compute the additional costs to connect these to the nearest transformer. Figure 2 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 potential. The maximum potential shown for each scenario is what would be

<sup>2</sup> A wind polygon is a suitable area for onshore wind, with space for one or more turbines, derived as outlined in the methods section.

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. Roughly half-way between these two extreme scenarios are the arguably much 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 and overall costs and potentials, around 1400 TWh and £ 210 billion in the case of *Wind\_parks\_LCOE*, and 1718 TWh and £ 277 billion in the case of *Wind\_parks\_Eyield*. Comparing the latter two scenarios with the scenario without connections (*Turbine\_no\_conn*) reveals an approximate difference in total costs of £ 187 billion to realize the full potential. Expressed as a marginal cost, this equates to a difference between £ 0.16 billion/TWh and £ 0.06 billion/TWh. In other words, the marginal costs per TWh more than double if network connection costs are considered.

## Impacts of scenicness on wind planning applications

To study the association between the scenicness and the planning outcome of energy projects, we use two main data sources. First, we measure scenicness using crowdsourced scenic ratings from *Scenic-Or-Not* (<http://scenicornot.datasciencelab.co.uk/>). *Scenic-Or-Not* presents users with random geotagged photographs, most of which have been taken at eye level, each representing one square kilometre of Great Britain. 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 web-based project that aims to collect and reference geographically representative images of every square kilometre of the British Isles. The final *Scenic-Or-Not* database has 217,000 images covering nearly 95% of the 1 km squares of land mass in Great Britain. The resulting *Scenic-Or-Not* dataset contains 1,536,054 ratings for 212,212 images. Here, we analyse the mean scenicness values for all photos rated 3 times or more.

The second primary data source is the Renewable Energy Planning Database, which contains detailed data about renewable energy applications in Great Britain.<sup>38</sup> Using detailed GIS information, 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 2 shows the results of the logit regression. Model 1 includes only the scenicness value, whereby the associated estimated odds ratio is below one (estimated coefficient is negative) and significant. In the following models 2-4 we sequentially introduce the year fixed effects, the project technical attributes, 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 preferable specification, whereby the odd 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 0.22 decrease in the log-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.

**Table 2 | Logit regression results (odds-ratio) for wind project planning outcomes**

	Model 1	Model 2	Model 3	Model 4	Model 5
Scenicness value	0.850*** (0.033)	0.793*** (0.034)	0.769*** (0.036)	0.781*** (0.037)	
Number of turbines			1.231*** (0.031)	1.228*** (0.031)	1.221*** (0.030)
Capacity (MW)			0.934*** (0.008)	0.935*** (0.008)	0.935*** (0.008)
log distance to the closest National Park				1.173*** (0.068)	1.215*** (0.069)
log distance to the closest airport				0.988 (0.112)	0.943 (0.105)
log distance to the closest Special Protection Areas (SPA)				0.965 (0.042)	0.919** (0.039)
log distance to the closest Special Areas of Conservation (SAC)				0.889* (0.054)	0.906 (0.054)
log distance to the closest Ramsar areas				1.028 (0.061)	1.039 (0.061)
Year fixed effect	no	yes	yes	yes	yes
Constant	2.626*** (0.449)	1.296 (1.610)	1.668 (2.122)	1.634 (2.249)	0.822 (1.137)
Number of observations	1,324	1,324	1,324	1,324	1324
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

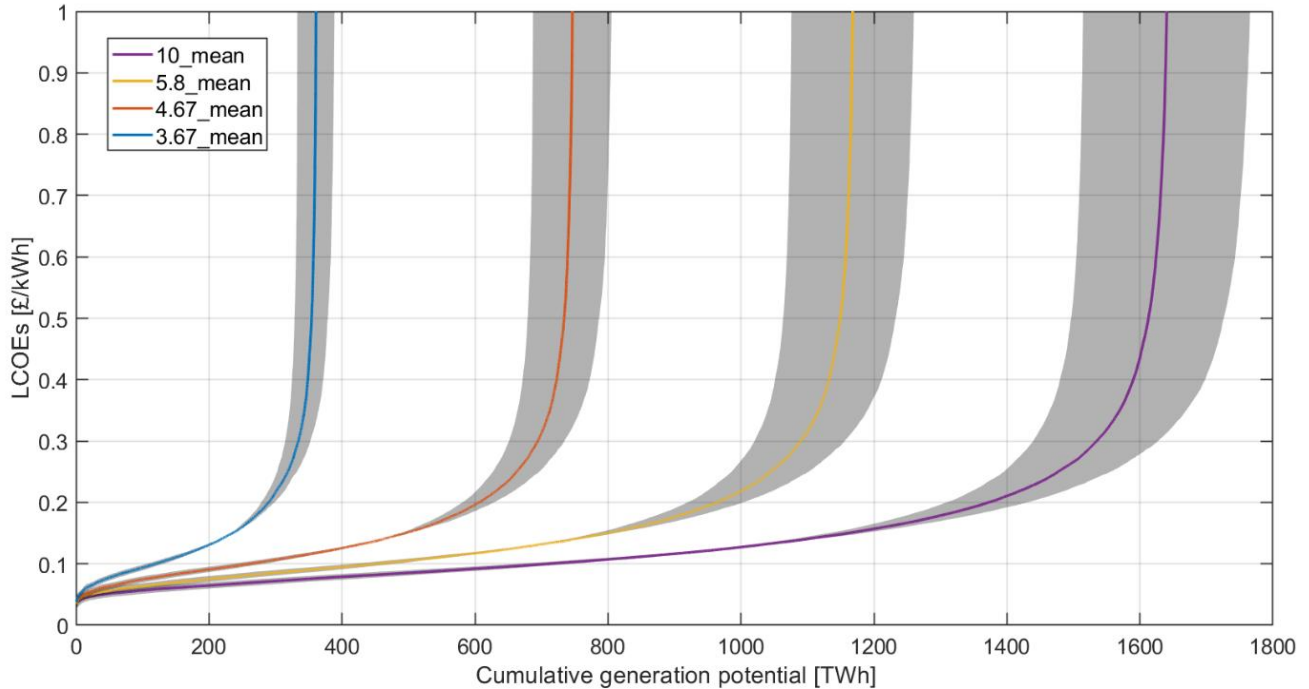
Note: discrete dichotomous variable taking a value of 1 if the application decision is positive, otherwise 0; \*\*\*, \*\*, \* indicate that estimates are significantly different from zero at the 0.01, 0.05 and 0.10 levels, respectively; standard errors are in parentheses. AIC is Akaike's<sup>39</sup> information criterion. Akaike weights represent the minimized Kullback–Leibler discrepancy, given the data and the set of candidate models.

Turning to the 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.<sup>40</sup> also find a positive correlation between the number of turbines and the positive application outcome, and Roddis et al.<sup>41</sup> 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 given capacity and the other included variables.

## Consequences of scenicness for onshore wind potentials

The overall results show a potential area of 80,500 km<sup>2</sup> (around 38% of Great Britain's land area) and a generation potential of up to 1718 TWh. To facilitate interpretation of the results, we firstly focus on one scenario (*Wind\_parks\_Eyield*) and present the cost-potential curves for tertiles of the scenicness distribution, as well as the maximum value

(i.e. 10), cf. Figure 3. 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 and 1173 TWh up to 5.8.



**Figure 3 | Cost-potential curves for four scenicness thresholds 3.67, 4.67, 5.8 and 10, showing minimum, mean and maximum ranges for the wind years of 2001-2006 in Great Britain.**

Figure 4 illustrates the relationship between the average (mean) normalized LCOEs within discrete (integer) values of scenicness. For the scenario *Turbine\_no\_conn* there is a clear inverse relationship between the average LCOEs and the scenicness values, approximated with a linear function ( $R^2 = 0.92$ ). This suggests a strong correlation between the “best” wind resource (in terms of wind speeds and hence LCOEs) and high scenicness values. In both scenarios with connections to transformers, the average LCOEs exhibit a peak at scenicness values of 9. This is thought to be due to the aforementioned colocation: the most scenic sites tend to be more “rural and wild”<sup>28</sup>, 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 located far from the nearest transformer, as they tend to more urban and/or industrial areas.

Also shown in the figure is the cumulative generation potential across the full range of scenicness values (*Wind\_parks\_Eyield* scenario). It is clear from this curve that scenicness values above 7 hardly contribute to the total potential and above this value the network connection costs increase. Partly this is due to only 7% of the values having such high votes (i.e. greater than or equal to 7), partly it is due to some of the sites with very good wind resources being excluded anyway, e.g. due to being in national parks, conservation areas etc.

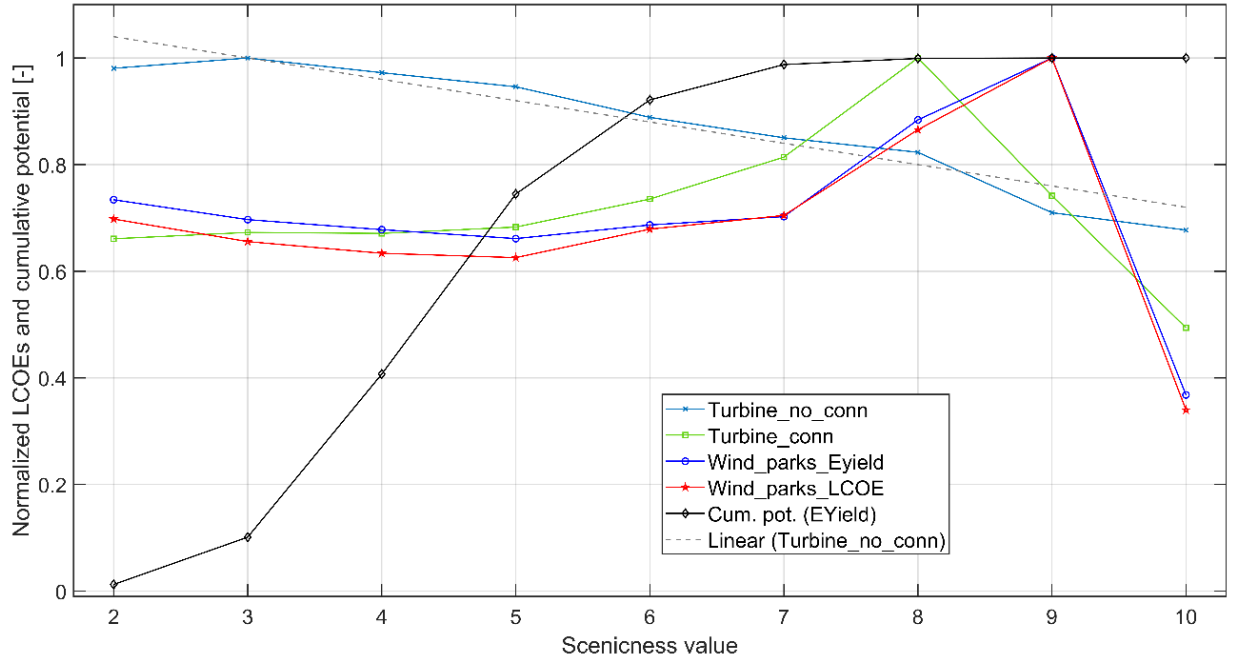


Figure 4 | Normalized mean LCOEs and cumulative generation potential across all scenickness values (linear regression:  $LCOE = -0.04 \text{ scenickness} + 1.12$ ,  $r^2 = 0.92$ ).

## Discussion

The results of this study are in broad agreement with the literature. In terms of total suitable area, we identified 38% of Great Britain's land area, somewhat higher than Ryberg et al.<sup>3</sup> who found 24% of UK (28% of GB) and McKenna et al.<sup>35</sup> with 18% (21% of GB). McKenna et al.<sup>35</sup> found total costs of about € 70 billion (about £ 50 billion at then-current rates) for around 1274 TWh (or 466 GW), which corresponds well with the *Turbine\_no\_conn* scenario here. In our base case (*EYield*), we determined 1717 TWh and 763 GW as the generation potential and installed capacity respectively. This is relatively high compared to McKenna et al.<sup>35</sup>, but much closer to the more recent study of Ryberg et al.<sup>42</sup>, who found 2262 TWh and 690 GW potential. The only other recent study to analyze Great Britain<sup>1</sup> 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.<sup>43</sup>

The first novelty in this paper is using OSM and CORINE data to improve the accuracy, as demonstrated above. Validation of OSM data shows that the completeness of street data is high (>95%) for most Western European countries.<sup>44</sup> But in comparison, the completeness of building information in OSM is typically much lower; example estimates include 23% for Saxony, Germany in 2013<sup>45</sup> and 57% for Lombardy, Italy.<sup>46</sup> This may have resulted in overestimates of the area suitable for wind farms in our calculations.

The second novelty is the consideration of the network connection costs. The 2752 transformer locations were extracted from OSM but could not be validated, meaning a high level of uncertainty associated with their number and location. The consideration of these connection costs is intended to go some way towards employing "system costs" of onshore wind as a metric to assess suitable and economic locations. But the connection costs form only one part of the system LCOEs.<sup>29,30,31</sup> In order to assess the full system level integration costs, the balancing and profiling costs should also be considered in the

context of reduced future costs for wind energy.<sup>47</sup> Here, we show the cost implications of excluding scenic locations from onshore wind developments, whereas Price et al.<sup>32</sup> for example demonstrate that excluding scenic locations has a significant impact on the system costs.

The introduction of a quantitative measure of environmental aesthetics using data from *Scenic-Or-Not* is the third and central innovation in this study. Visual impact has long been recognised as a concern when considering the installation of new onshore wind facilities.<sup>12</sup> However, a lack of data has previously made large-scale, quantitative analysis of this location characteristic challenging. Future studies could look to improve on this quantitative measure further. For example, *Scenic-Or-Not* continues to collect ratings of these photos, such that the mean of just over 7 votes per picture in the current dataset will grow in the future, thereby further increasing data reliability. The data could be further augmented using the deep learning model introduced by Seresinhe, Preis and Moat<sup>48</sup>, trained on *Scenic-Or-Not* and able to automatically assess the scenic appeal of photographs. Further crowdsourced ratings or deep learning estimates would make it possible to increase data granularity above one photograph per 1 km<sup>2</sup>. Ratings for further photographs would also help ensure that views in different directions were taken into account for each area.

Even with such potential improvements however, we note that ratings of photographs are likely to be influenced by temporary features of a scene, such as the weather, as well as the skill of the photographer, as manifested in qualities such as image composition. These influences will add noise to the dataset. A further concern relates to how users of *Scenic-Or-Not* may have interpreted the core construct of 'scenic', although the sensitivity analyses in the methods section reduce this concern. Earlier analyses of the *Scenic-Or-Not* data do 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<sup>27</sup>, and indeed that man-made structures can in some circumstances boost the aesthetics of a scene.<sup>48</sup> For example, while the presence of wind farms in a photograph was found to reduce scenic appeal, the presence of other sizeable man-made structures such as viaducts, castles and lighthouses was found to increase the scenic rating of a photograph.<sup>48</sup>

We explore the relationship between scenicness and onshore wind potentials in a British context within a quantitative spatial framework. To extend this approach to other countries, either a set of images of the environment taken at eye-level is needed, or a relationship between scenicness and land use categories.<sup>49</sup> Scenic ratings of the images could then be crowdsourced using a similar approach to *Scenic-Or-Not*, or estimated using computer vision approaches.<sup>48</sup> This framework could also be enhanced to consider the size and type of turbines installed, introduce a setback distance that can strongly increase acceptance<sup>20,21,22,23</sup> or account for the experience that local communities already have with wind energy.<sup>21,24,25,26</sup> It 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.<sup>28,29</sup>, to help policymakers understand the range of trade-offs at play.

It is also important to stress that wind energy should be considered in the context of other alternatives and their like-for-like impacts across all categories.<sup>50</sup> 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.<sup>51,52</sup> Ultimately, research on social acceptance of wind energy is highly heterogeneous with some contradictory findings<sup>24</sup>, which encourages widening the scope of this research to consider additional perspectives.<sup>53</sup> To relieve the tension between ambitious energy system transformations and democratic social process<sup>54</sup>, trade-offs will have to be made at all levels.

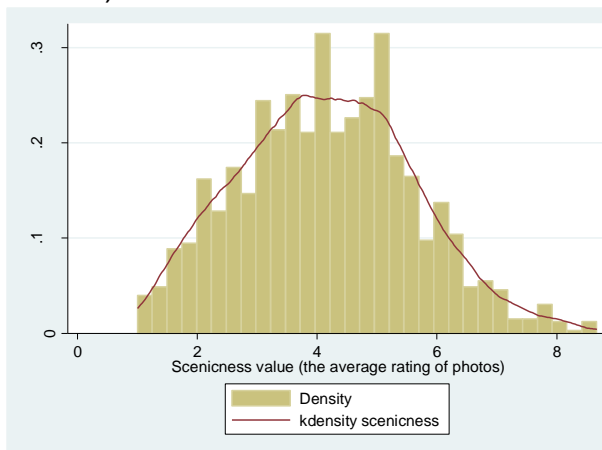
## Conclusions

To conclude, we return to the research questions posed at the outset. Firstly, the accuracy of onshore wind potential assessments can be significantly increased by employing OSM alongside CORINE data, in this case by about 30%. Secondly, the grid connection costs vary strongly depending on location but on average increase the LCOEs of onshore wind by 100%. Thirdly, planning applications for onshore wind are less likely to be accepted in more scenic locations. We also found that there is a strong correlation between scenicness and the ‘quality’ of the wind resource. 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 and social benefits.

## Methods

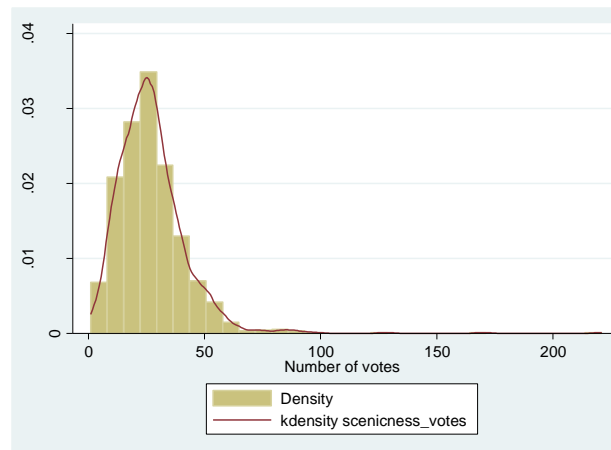
### 1. Regression of planning applications’ outcomes and scenicness

In addition to the scenicness data, we also employ the Renewable Energy Planning Database, 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 4).



**Figure 5 | Frequency distribution of scenicness values**

*Notes: Number of observations is 1324; kernel = epenechnikov, bandwidth = 0.3134.*



**Figure 6 | Frequency distribution of scenicness, number of votes**

*Notes: Number of observations is 1324; kernel = epenechnikov, bandwidth = 2.6142.*

In this analysis, we use the mean rating of images that have been rated at least three times, a total of 145,965. The scenicness values are in the range from 1 to 8.7 with the mean value of about 4. There are only a few high scenicness values (99% percentile is 7.8), see also Figure 5. 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 27 (Figure 6 and Table 3).

**Table 3 | Distribution of scenicness votes employed in this study**

Scenicness	1	2	3	4	5	6	7	8	9	10	Total
<b>Number of votes</b>	11,850	27,233	44,346	51,266	39,517	23,251	10,804	3,455	483	7	145,965
<b>Fraction of votes</b>	0.06	0.13	0.21	0.24	0.19	0.11	0.05	0.02	0.00	0.00	1.00

The sample also includes other relevant variables that have been selected following findings in Roddis et al.<sup>41</sup> and Harper et al.<sup>40</sup> These variables are computed from protected sites data extracted from the Joint Nature Conservation Committee website<sup>55</sup> and the National Parks data from the Office for National Statistics.<sup>56</sup> 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 4 | Descriptive statistics of Renewable Energy Planning Database**

	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	26.147	15.985	28.363	14.202
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.

Table 4 shows summary statistics for the final sample of planning applications used for estimation. The mean number of votes is also somewhat higher for rejected applications<sup>3</sup>. 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

<sup>3</sup> The difference between the mean number of votes for applications with a negative and a positive outcome is 2.216 (28.363- 26.147).  $H_0: diff \neq 0. Pr(|T| > |t|) = 0.009$ .

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  $t$ :

$$\Pr(D_{i,t} = 1 | S, \mathbf{X}; \alpha, \beta, \boldsymbol{\delta}, \boldsymbol{\gamma}) = F(\alpha + \beta S_{i,t} + \boldsymbol{\delta}'\mathbf{X}_{i,t} + \boldsymbol{\gamma}_t) \quad (1)$$

where  $D_{i,t}$  denotes the discrete dichotomous variable taking a value of 1 if the application decision is positive, otherwise 0;  $\alpha$  is a constant term and  $\boldsymbol{\gamma}$  is the year fixed effect;  $S_{i,t}$  is the scenicness value; and  $\mathbf{X}_{i,t}$  denotes controls for project characteristics such as technical and geographical attributes. The coefficients 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<sup>4</sup>. We are particularly interested in the value of  $\beta$ , 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.

**Table 5 | Sensitivity analyses: logistic regression results for project planning outcome**

	Model 1 Wind energy probit	Model 2 Wind energy logit <sup>\$</sup>	Model 3 Solar energy logit
Scenicness value	-0.148*** (0.028)	-0.220*** (0.056)	-0.030 (0.054)
Number of turbines	0.121*** (0.014)	0.229*** (0.028)	
Capacity	-0.040*** (0.005)	-0.073*** (0.009)	-0.013 (0.008)
log distance to the closest National Park	0.093*** (0.033)	0.169*** (0.061)	0.101* (0.060)
log distance to the closest airport	-0.001 (0.068)	0.001 (0.124)	0.209** (0.090)
log distance to the closest Special Protection Area (SPA)	-0.022 (0.026)	-0.024 (0.047)	-0.030 (0.096)
log distance to the closest Special Areas of Conservation (SAC)	-0.072** (0.036)	-0.085 (0.064)	-0.282*** (0.081)
log distance to the closest Ramsar areas	0.015 (0.035)	0.033 (0.063)	0.026 (0.082)
Year fixed effect	yes	yes	yes
Constant	0.240 (0.856)	0.207 (1.411)	0.612 (0.682)
Number of observations	1,324	1,169	1,558
AIC	1425.84	1254.61	1422.88
Log likelihood	-688.92	-604.31	-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. *AIC* is Akaike's<sup>39</sup> information criterion. <sup>\$</sup># votes > 11 (10% percentile).

<sup>4</sup> A particular advantage of the logit model over the linear probability models is that it has a choice theoretic interpretation.<sup>57</sup>

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<sup>40,41</sup>, see Table 4 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 5. 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 modeled as a linear combination of the predictors. The estimation results are reported in Table 5 Model 1. The estimated coefficient associated with the scenicness value is negative and significant. Model 2 in Table 5 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 11 (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 15 (25% quartile) and 25 (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 5 Model 3).

## **2. Estimating onshore wind potentials and network connection costs**

### **a. Determination of the feasible area for onshore wind**

The general approach to determining feasible areas and technical generation potentials for onshore wind in the UK follows the one in McKenna et al.<sup>35</sup>, with two main differences:

1. The suitable areas and offset distances for onshore wind turbines are taken from the cited source. In the current paper we employ Open Street Map (OSM) alongside Corine Land Cover (CLC), whereby each dataset generates positive (suitable for onshore wind) and negative (unsuitable) areas. We then perform two steps to exploit the advantages of using two datasets. Firstly we calculate a new area  $A = OSM_{pos} - CLC_{pos}$ , to account for the incorrectly excluded areas according to CLC. Secondly, we calculate a new area  $B = CLC_{pos} - OSM_{neg}$ , in order to account for (small) negative areas within the positive CLC areas. Finally we take the union of A and B to arrive at a total geographical potential.
2. The wind data employed consists of monthly mean wind speeds for the years 2001-2006 at 5 km<sup>2</sup> spatial resolution.<sup>58</sup> In Figure 3, we plot the minimum, mean and maximum potential values for the six analysed weather years (2001-2006). These years have an average capacity factor for onshore wind of 24%, which broadly correspond to the long-term average in the UK.<sup>37</sup>

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.



## b. 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](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.*"](.a);
  way["power"="substation"]["voltage"~".*132000.*"](.a);
  relation["power"="sub_station"]["voltage"~".*132000.*"](.a);
  way["power"="sub_station"]["voltage"~".*132000.*"](.a);
  relation["power"="station"]["voltage"~".*132000.*"](.a);
  way["power"="station"]["voltage"~".*132000.*"](.a);
);
out qt;>;out qt;
```

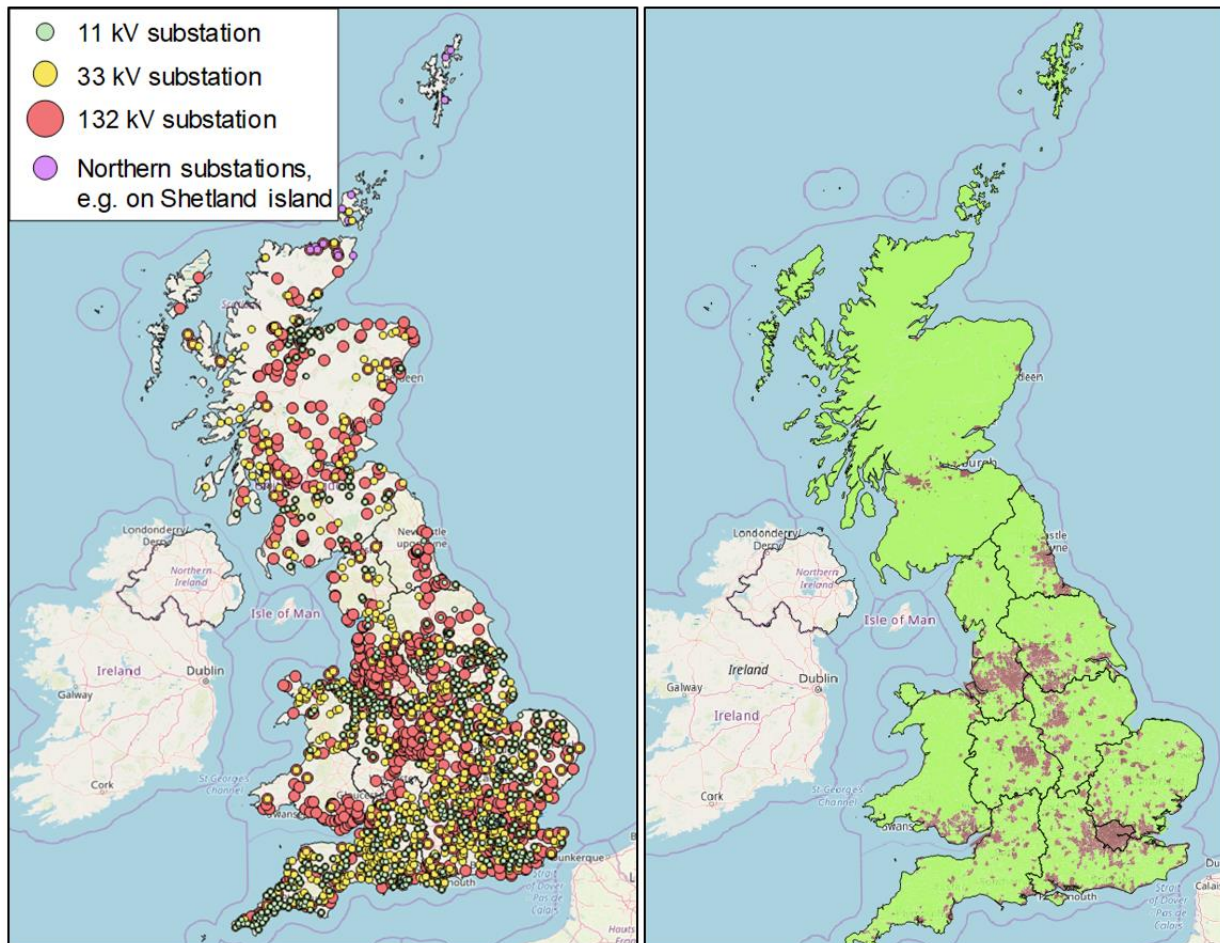


Figure 7 | Transformers, which are tagged in OpenStreetMap, as well as area classification in the UK. The comparison of the locations of transformers (left part of figure) and urban areas (brown shapes, right part of figure) shows, that those transformers are predominantly located near urban areas.

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](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. Subsequently, the GeoJSON file was imported into QGIS and the coordinates of the centroids of the transformer-polygons were determined.

This procedure resulted in 964 transformers with 132 kV, 1115 with 33 kV and 673 with 11 kV (cf. left part of Figure 7). For the northern part of UK (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 7 and only one transformer is visible for the relevant location.

### c. 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 6. 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 6, however, the interval for 132 kV only reaches 240 MW, since the National Grid cost estimator only indicates costs up to this value.

Table 6 | 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 classification	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

#### d. 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 7, there are significantly more urban areas (brown shapes) in England than in Scotland and Wales. The single polygons in these area classification shapes were then merged to accelerate the computing processes. The distances between the wind farms and the transformers were then calculated. We use two different definitions for these wind farms in two cases, which are explained in Sections 3.e and 3.f respectively.

#### e. Separate consideration of wind polygons<sup>2</sup>

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 8 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 8 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.

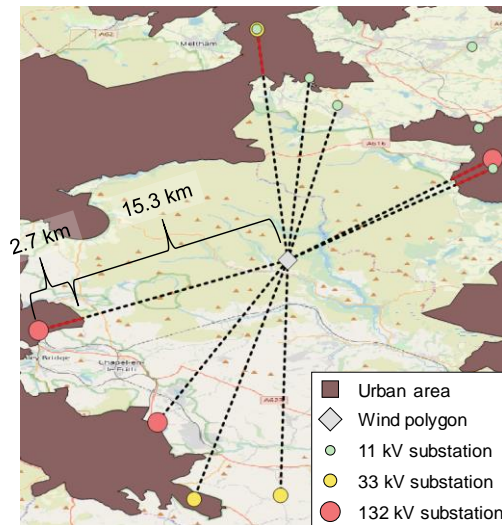


Figure 8 | Possible connection lines of one wind farm to the nearest three transformers of each voltage level. The red part of the lines leads through urban areas.

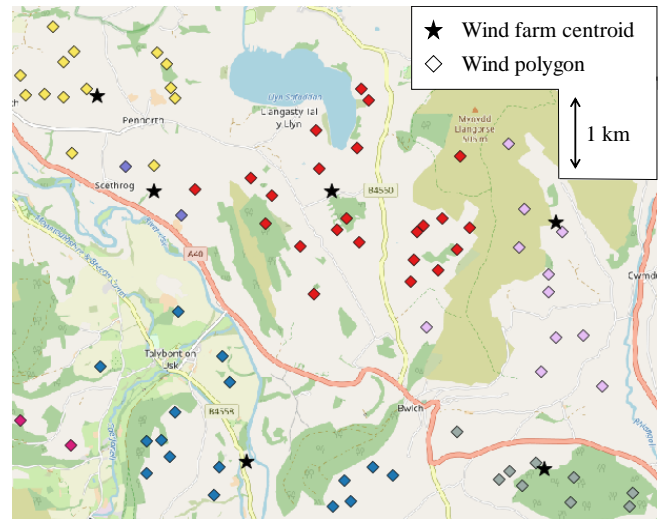


Figure 9 | Combination of wind polygons to wind farms for a specific area in UK. The colours of the wind polygons indicate different wind parks.

The generation capacity of the wind plants is derived from the product of the geographical potential (available area in km<sup>2</sup>) with the turbine-specific power density (in MW/km<sup>2</sup>). 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.<sup>35</sup>) 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 system LCOEs due to a higher energy yield.

#### **f. Clustering wind polygons into larger wind farms**

If connection costs are included in the costs of small wind farms, this can significantly increase the LCOE. Therefore, 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 6). When combining the wind parks, the maximum possible capacity is assigned to each wind polygon, i.e. the turbine with the highest capacity density is employed (23.24 MW/km<sup>2</sup>). This results in 29,060 wind farms with capacities between 1.9 MW and 240.0 MW (mean value = 231.2 MW). Figure 9 shows resulting wind parks for a specific area in UK. 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 3.e, 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 system LCOE. The distance of the centroid of the wind farm (cf. stars in Figure 9) 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*).

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