Onshore wind and the likelihood of planning acceptance: learning from a Great Britain context

Michael Harper, Ben Anderson, Patrick James, AbuBakr Bahaj

Abstract

Geospatial modelling is extensively used to identify suitable sites for the installation of onshore wind turbines. However, there are concerns that such approaches do not accurately consider the social issues surrounding such projects, resulting in large numbers of projects subsequently being rejected at planning permission. Using the location of 1691 historic wind turbine planning applications in Great Britain, this paper explores whether the planning success of proposed wind turbine projects can be predicted using a range of geospatial, social and political parameters. The results indicate that the size of the project, percentage of the local population with high levels of qualifications, the average age, and the proximity to existing wind turbines are key influences affecting planning approval. The paper demonstrates that quantitatively linking regional social and political data enhances the assessment of the planning outcome of wind turbines, and highlights that geospatial parameters are in themselves limited in identifying the suitability of sites. This suggests that existing policy is…

Keywords

Onshore Wind, Logistic Regression, Planning, Demographics, Great Britain, GIS

Word Count: 5110

1 Introduction

Increased environmental concern and issues surrounding security of energy supply have led to a global drive to develop renewable energy systems. Over $40 billion is invested annually within the European Union, with this figure expected to exceed $60 billion by 2020 [1].

Whilst many renewable energy technologies are available, onshore wind is is one of the most established technologies and offers one of the least-cost options for renewable energy supply. For example, the cost projections for new onshore wind projects in the United Kingdom in 2020 are projected to be between £47-76/MWh, a price which competes with conventional fossil-fuel technologies [2]. This economic viability is coupled with a high resource availability, with the UK and many other European countries having a large exploitable wind resource [3].

Despite the strengths of onshore wind energy, development of the technology is restricted as there are challenges for proposed projects to receive planning permission. Proposals often face local opposition, with visual impact, noise, site access and ecological impacts often being cited as reasons for objection [4,5]. These planning challenges are particularly evident in the United Kingdom, where 52% of onshore wind projects are refused permission or are abandoned by the developer [6]. As highlighted in Figure 1, this rate is signficantly higher than for other renewable energy technologies in the UK.

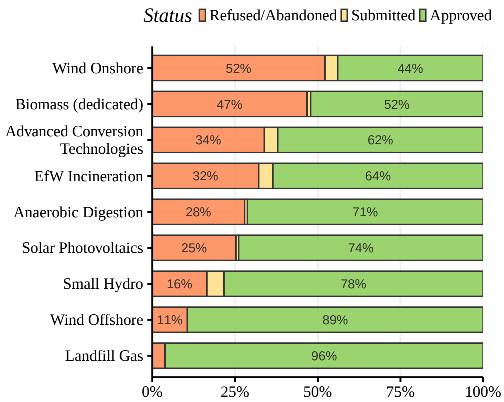

Figure 1: Acceptance rates of renewable energy projects within the UK between 1991 and 2017. The Analysis only considers technologies which have had more than 50 planning applications.

Whilst planning has been a persistent issue for wind turbines, recent changes in legislation have severly impacted the development of onshore wind. Until June 2015, the planning decision for projects greater than 50MW was controlled at a national level. However, this provision was removed by the *Energy Act 2016* and *Infrastructure Planning Order 2016*, which provided local authorities with the final say for all onshore wind energy projects [7]. In addition, these wind turbines are only permitted in sites which have been identified within neighbourhood development plans. These changes have effectively enabled local communities to be in a position to block the development of wind turbines in their area.

In addition to changes in planning law, the development of onshore wind has been further restricted by changes to the financial mechanisms used to support low-carbon energy in the UK. Onshore wind projects were removed from the Renewable Obligation scheme on 1st April 2016 [@], preventing projects from bidding in the upcoming £557 million (date:) in subsidies [@].

As a result these planning and financial changes, there has been a dramatic reduction in the development of onshore wind since 2016. In June 2015, the month the changes in planning were implemented, there were 133 planning applications for onshore wind, a record high for a single month [6]. In contrast, for the entire year of 2017, there were only 52 planning applications made, representing only 6% of the 2015 total. This reduction in planning is highlighted in Figure 2.

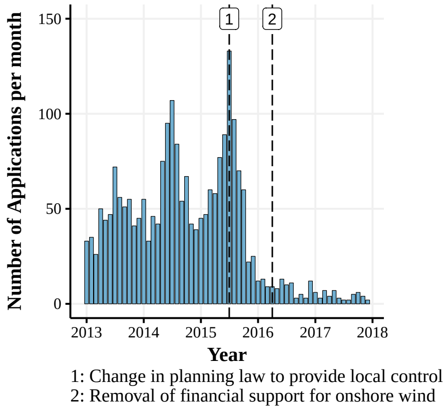

Figure 2: Number of turbine planning applications submitted in the United Kingdom per month between January 2013 and December 2017.

The planning and financial changes changes have increased the barriers to project development, and reflect the importance of considering local communities within the proposals of onshore wind projects. The UK is not alone in experiencing in encountering opposition to wind turbine projects [5], but is perhaps unique in how policy has been restructured to restrict its development.

This paper looks to understand if existing geospatial modelling of onshore wind can account for the low levels of acceptance of onshore wind in the UK (Figure 1). This paper explores existing social and demographic parameters which can be used to enhance acceptance rate prediction for the site.

2 Background

2.1 Geospatial Modelling

To assist in the development of onshore wind energy, many methodologies have been produced to determine site suitability for wind farms. Development primarily started within the late 1990s [8,9], and established a structure which has been applied extensively internationally [10–25]. These methodologies combine geospatial modelling with Multi-criteria Decision Analysis (MCDA) techniques to identify sites which are deemed suitable for development [26].

When determining suitable sites for development, ideal sites are typically identified as 1) *having high average wind speeds*; *2) not being close to urban areas*; *3) not in protected landscapes (e.g. National Parks)*; *4) not close to airports (to minimise radar interference)*; *5) close to roads for access* and *6) close to power lines for grid connection*. However, there are concerns that geospatial parameters in isolation are in themselves insufficient to explain patterns of development of wind turbines [27]. These concerns can be further supported by the continued reductions in the acceptance of wind turbine projects in the UK, shown in Figure 3, suggesting there is a widening gap between existing modelling approaches and real world development patterns.

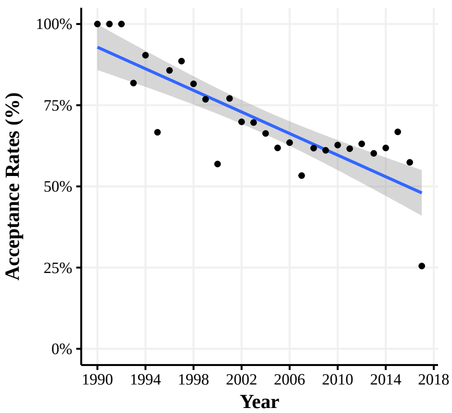

Figure 3: Annual Average Acceptance rate of wind turbine projects within the UK

Whilst some studies compare the resulting suitability maps with locations of operational wind turbines [15,16,18,20,22], these were largely used only as a form of discussion, and the information was not directly used to develop or revise the models. This overlooks a valuable contribution that existing sites could provide in understanding whether there are any spatial development patterns which can be identified. In particular, Watson [22] noted "*operational wind farms in South Central England were predominantly located in areas suggested to be of lower suitability*", suggesting that the model inaccurately assesses site suitability in the region.

In situations where there is a large enough sample of similar historical spatial decisions, an "*Inverse theory*" approach can be applied to determine subjective valuation of criteria by stakeholders [28]. Compared to the traditional "*Forward theory*" approach of geospatial modelling (Figure 4a), an inverse approach assesses the existing spatial distribution of projects to determine the most influential parameters in determining site success (Figure 4b). Such an approach has been used successfully within public health studies [29–32] and infrastructure location decision-making [33,34] to determine optimal sites for development.

2.2 Planning Acceptance Parameters

The difficulties in receiving planning permission for onshore wind turbines has prompted research to assess the factors which influence the public acceptance of onshore wind turbines. It has been highlighted that the acceptability of wind energy projects is based on more than just geospatial parameters [5,27,35]. In a review of 146 journal articles of planning acceptance, perceptions and attitudes towards wind turbines, Langer et al [5] summarised that parameters can be grouped into three groups 1): *Physical and*

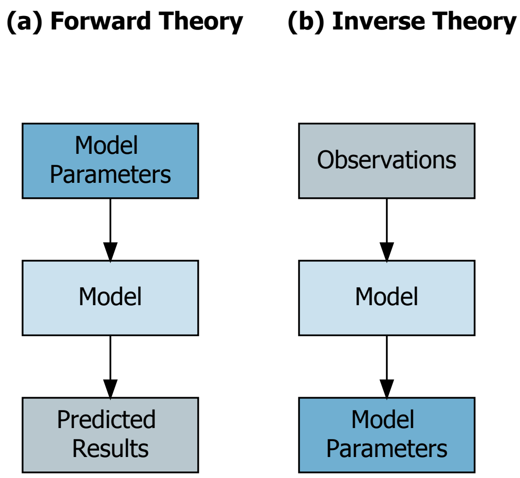

Figure 4: Comparison of Forward and Inverse GIS MCDA model structures

Environmental; 2) *Pyscho-social* and 3) *Social and Institutional*.

Qualitative surveys are used to explore potential factors which influence planning acceptance. A key concept consistently investigated within empirical research is the *"proximity hypothesis"*, which states that those living closest to a wind farm will have the most negative perceptions of it [36,37]. However, attempts to prove this hypothesis have largely proved unsuccessful, and results have proved conflicting. For example, evidence from Denmark suggests no link between proximity of residential properties to the nearest turbine and negative public perceptions, with suggestions that respondents living closest (i.e. within 500 metres) actually had more positive perceptions in comparison with individuals living away from turbines [38]. This view was further supported by a study in Cornwall, UK, which found that local communities with visibility of the turbines were generally more supportive of wind turbines [39]. However, several studies have reported the opposite relationship [40,41], with the studies finding that negative perceptions increased with proximity to wind energy developments.

Literature has also sought to understand the potential cumulative effects that wind turbines have, as projects are frequently refused planning in regions already containing wind turbines [39,42,43]. However, there has been limited understanding in how neighbouring wind energy projects may alter the likelihood of nearby wind turbine projects receiving planning, and current research has focussed on smaller case studies [43].

It has been argued within literature that psycho-social factors have become crucial dimensions to explain how local communities interact with, and react to, new wind farm developments [5]. The effects of socio-demographic variables on individuals' views of wind farms have also been studied within literature [36,44]. Age, gender, experience with wind farms, and use of the land and/or beach were found to be slightly correlated with the attitudes towards wind power in a Danish study dealing with public perceptions of onshore or offshore wind energy projects.

At an individual level, empirical findings suggest that political beliefs are correlated with social acceptance of different low carbon technologies [45]. This is supported by surveys that indicated that only 62% of individuals indicating support for the Conservative party were supportive of new renewable energy developments, compared to 86% and 84% for Labour and Liberal Democrats respectively [46].

Studies have highlighted that the interaction of developers with local communities are key indicators of positive planning approval outcomes [47–49]. Projects which seek greater approval within their plans are generally more successful than those which are fixed prior to consultation with the local population.

Finally, the ownership structure of a project has been indicated to be a significant influence on the level of public acceptance [50,51]. Projects are generally seen as more favourable when owned by local energy cooperatives than by a large energy company or investor with no local connections. This reason has been raised to explain the differences in project success between the United Kingdom and Germany [35].

2.3 Quantitative Analysis of Turbine Acceptance

There has been increased use of quantitative analysis to quantify the effect parameters have on the outcome of wind energy planning outcomes. Such approaches build upon the understandings provided within the qualitative analysis explained with Section 2.2, and aim to provide numerical data that can be transformed into usable statistics.

Toke [47] conducted logistic regression analysis using data collected for 51 wind energy sites within the UK, and explored how planning outcomes were influenced by the views of key actors within the planning process of wind energy, including local councils, planning authorities and landscape protection groups. The study found that planning acceptance rates were closely associated with the high level of apprehension about such schemes amongst people living in the immediate vicinity, highlighting the importance that social influences have on planning acceptance.

Van der Horst and Toke [27] assessed how local characteristics related to the planning outcome of wind energy projects in England. 117 variables related to education, health, demography, employment and housing were used and compared with the planning outcomes for 77 wind energy projects. Univariate regression analysis was conducted with the Mann-Whitney test being used to analyse the associations between the planning decision outcome and each of the independent variables separately. Several strong associations were identified for planning refusal, including (1) *voter turnout* and (2) *years of potential life lost*[1]. The study notes that wind energy appears to generally be more likely to receive planning permission in deprived areas, and as previously noted within the review, some developers were "*keen to*

[1] Years of potential life lost (YPLL) is an estimate of the average years a person would have lived if he or she had not died prematurely. It is, therefore, a measure of premature mortality.

avoid relatively privileged communities and target areas where people are thought to less likely put up a fight” [27]. These issues highlight the potential importance of social parameters in site selection.

Van Rensburg et al. [52] utilised adjusted probit regression to assess the relative magnitudes of association amongst wind farm project planning approval against a range of 66 variables including project technology, institutional processes and site endowment. Information was collected from 354 wind farm applications and planning authority decisions between 1990 and 2011 in Ireland. The results suggested a range of variables which appeared significant for planning, including 1) *proximity to Natura 2000 sites*; 2) *sites with high bird sensitivity*; 3) *hub height* and 4) *project capacity.* In addition, the study noted that proximity of the nearest dwellings and wind speeds appeared insignificant, which is counter to the view reported within many previous studies. Of the variables included within the model, it concluded a 0.31 predictive confidence value.

2.4 Combining GIS and Quantitative Research

Whilst studies suggest a relationship between demographic and social data and wind turbine planning acceptance rates, none of geospatial models reviewed attempted to integrate these into their assessment beyond the use of proximity buffers around urban areas. It is argued that this omission fails to fully factor in the social dimension in terms of its impact on the suitability of sites for development.

Existing quantitative studeis highlight the value which can be provided by assessing previous planning applications. However, these projects have been limited in the number of projects considered and the parameters considered. Responding to calls to combine qualitative and quantitative research [5], this paper presents analysis which assesses parameters that influence wind turbine planning outcomes, utilising a range of physical, geographical, demographic and political parameters.

3 Material and Methods

The overall methodology is highlighted in Figure 5, with a detailed explanation provided in the following subsections.

3.1 Study Scope

The study was conducted across Great Britain (England, Scotland & Wales). These were chosen due to the broadly similar categorisation of land types, nature designation, data availability and legislation across these regions [53]. The Shetland Islands were excluded from the analysis as their geographic isolation and distance from mainland Britain created issues in generalising the model results.

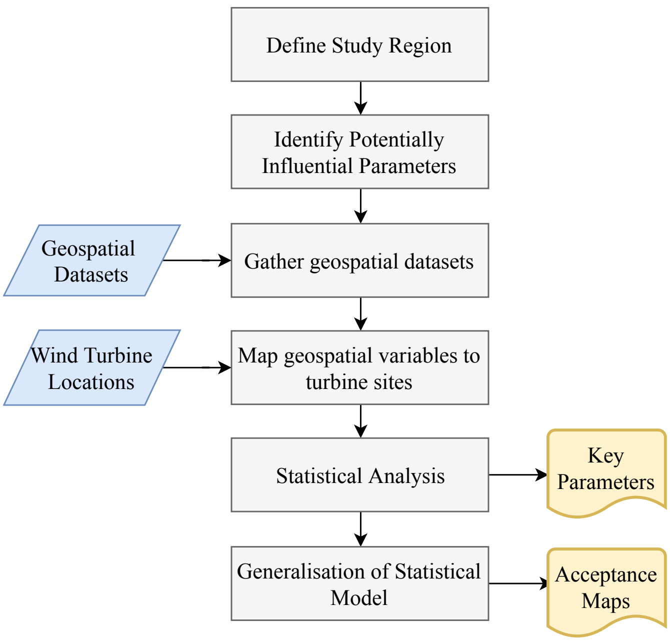

Figure 5: Research methodology

3.1.1 Wind Turbines Dataset

Information for turbine planning applications was collected through the Renewable Energy Planning Database (REPD) [6] with planning dates between January 1991 and December 2015 (n=1675). Detailed information for each planning application includes the location; year of application; number of turbines; turbine capacity and planning decision. The planning permission status was summarised to a dichotomous variable for use within the statistical analysis: 1) *Approved* and 2) *Refused/Abandoned*. The spatial distribution of these sites is highlighted in Figure 6.

3.1.2 Model Layers Data

Building upon the literature referenced in Section 1, data sources were identified for geospatial and social parameters which had been indicated to be influence wind turbine planning applications. A summary of the variables is provided in Table 1, with a full details provided within the Technical Appendix A.

- **Resource**: wind speeds were taken from the Numerical Objective Analysis of Boundary Layer (NOABL) wind speed database. This provides estimated annualised wind speed at 45m elevation at a resolution of 1km grid [54], and has been used in previous studies within the UK [9,22].
- **Features**: Physical features including roads, railways and urban areas were collected from OS Strategi [55]. The electricity transmission network, military sites and airport locations (civil and military) were extracted from Open Street Maps (OSM) [56].
- **Landscape and Nature**: Landscape and nature designations were collected for regions within

Table 1: Parameters considered within model

Category	Variable
Turbine	Wind Turbine Planning Data
	Turbine Capacity
	Number of Turbines
	Year
	Country
Resource	Wind Speed
Features	Airports
	Roads[a]
	Railways
	Urban Areas
	HV Powerlines[b]
	Military Sites
Landscape	Areas of Outstanding Natural Beauty
	National Parks
	Heritage Coast
Nature	Special Protection Areas
	National Nature Reserve
	Sites of Special Scientific Interest
	Special Areas of Conservation
Geographic	Elevation
	Slope
Census	Level of Qualification[c]
	Age
	Social Grade[d]
	Tenure
Political	Conservatives
	Labour
	Liberal Democrat
Proximity	Nearest Turbine (Operational)
	Nearest Turbine (Rejected)

[a] Roads are broken into four main categories: Motorways, A Roads, B Roads and Minor Roads

[b] High Voltage network at 140 400kV

[c] L4 represents degree level or above

[d] AB represents Higher and intermediate managerial, administrative, professional occupation

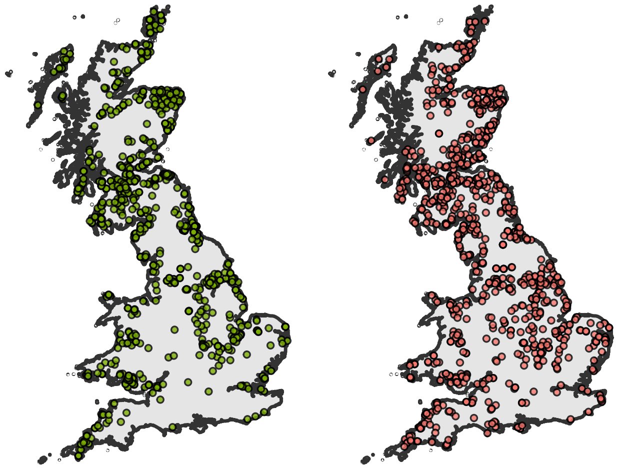

Figure 6: Location of onshore wind energy planning applications used within the study. Location data extracted from the Renewable Energy Planning Database (REPD)

the UK [57].

- **Geographic**: Site elevation data was collected at a 25m resolution [58]. This was used to calculate the gradient using the Fleming and Hoffer algorithm [59].
- **Census**: Census data was collected at the Lower Super Output Area (LSOA) and Data Zone (Scotland) which represents regions with a population between 1000 and 3000 people [60].

- **Political**: Political data was collected at the local authority level for the four largest parties in the UK: 1) *Conservatives*; 2) *Labour*, 3) *Liberal Democrat* and 4) - *Scottish National Party (SNP)*. These parties hold a sum of 95% of council seats within Great Britain as of 2016.
- **Cumulative**: the nearest wind turbine to the project was calculated using the location and year of planning application for each turbine.

It was not possible to collect bird sensitivity maps for the whole study region. Guidances states that this should be considered within the planning of projects [61].

- **Bird Mapping**:

3.2 Data Transformations

The data sources came in a varying spatial features, and were aggregated at each of the turbine locations as follows:

- **Points, lines and polygons**: A spatial join was completed to find the distance to the nearest feature for each turbine. For polygon based data source, value of 0km denotes the turbine is within the feature. Left censoring was used to limit the maximum distance of geospatial relationships to 30km, preventing extreme values from skewing the datasets.
- **Tabular**: corresponding political and census boundaries were used to map the tabular data, and turbines assigned the value of the region. In addition, political data was filtered to the year of the planning application to determine the political balance at the time of planning.
- **Raster**: The raster value at the site location was extracted.

In comparison to previous studies [52], no transformations were made to the standardise the dataset. Transformation provides no direct benefit to the model other than to allow a direct comparison to be made between the influence of parameters. In addition, model parameters create additional complication in the generalisation of the model results as models must transformed to the adjusted z-score scale to allow for comparison [62].

3.3 Statistical Modelling

A multiple logistic regression analysis was conducted to model the factors associated with a positive planning outcome of wind turbine applications using the predictor variables listed in Table 1. This model built upon the approaches developed by Toke et al. [47] and Van Rensburg et al. [52]. A hierarchical approach was applied to the model whereby parameters are added to the model sequentially based on the presumed importance of parameters. These were selected as follows:

1. **Aspatial Site Attributes**: variables including *Number of Turbines* and *Installed Capacity.*
2. **Economic Considerations**: parameters which influence the cost effectiveness of the site, including *Wind Speed* and *Proximity to the National Grid.*
3. **Temporal Aspect**: the year in which the planning application was made.
4. **Proximity to Features**: proximity to geographic features, Landscape and Nature Designations
5. **Social and Census Data**: Demographic data for the area of the wind energy project
6. **Political Data**: the political composition of the local authority composition at the time of the planning application.
7. **Spatial Proximity to Other Turbines**: the proximity to the nearest wind energy project.

For each additional set of parameters added to the model, diagnostic checks were made to ensure that the assumptions of logistic regression were maintained. Each parameter was checked for linearity of the logit for independent variables, absence of multicollinearity and independence of variables [62]. Any parameters which violated these conditions were removed from the model. The overall fit of the model was assessed using Pearson chi-squared, Psuedo R^2 values and the residual deviance. Internal validation was used to assess the predictive accuracy of the model, with a random sample of 5% fold size randomly selected and iterated 200 times. Once all parameters had been included within the model, a parsimonious model was produced to remove uninfluential parameters, with the Akaike Information Criterion (AIC) used to determine the best fitting model.

3.4 Regional Variation

Regional differences in parameters effects between England, Scotland and Wales were hypothesised due to differing population densities (England: 413/km^2, Wales: 149/km^2, Scotland: 68/km^2) [63] as well as differing institutional support, with Scotland in particular placing a greater emphasis on the development of onshore wind [6]. Where significant variation is expected within subgroups, split data models are recommended, whereby the dataset was segmented into groups based on model variables, and regression models are fitted to each subgroup [64].[2] Separate logistic regression models were produced, with the dataset split for each country. The parameters used to construct these models used two approaches. Firstly, the parameters from the parsimonious model were used across all three models ("*Global Parameter*"). In addition, an all-subset regression approach was used within each group to identify the best-fitting model within each group ("*Optimised Parameters*").

3.5 Generalisation

A spatial regression models was used to generalise the findings of statistical analysis, and are frequently used within geospatial modelling [65]. The outputs of the parsimonious regression model were used to generalise the results for national prediction. This model contained 13 variables, two of which were non-spatial parameters, *Turbine Capacity* and *Year*. To include these within the prediction, fixed values were assumed, and predictions made for the year 2017 with a turbine size of 2MW (the average model size for the given year [6]).

4 Results

The overall results for each stage of the hierarchical model are presented in Table 2. It can be seen that there is a marginal improvement of the Nagelkirke R^2 values across the results, and similarly the predictive accuracy of the model improves as more parameters are included. The final model reports a Hosmer-Lemeshow p-value of 0.032, which indicates that the null hypothesis holds for this model.

[2] Whilst a dummy variable could also be considered, such an approach only captures the *level* effect and not the *slope* effect, and therefore only allows for limited variability between the subgroups.

Table 2: A summary of the hierarchical logistic regression models

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Observations	1715	1715	1715	1715	1715	1715	1715
Parameters	3	5	6	22	25	28	31
Deviance	2350.57	2345.64	2248.33	2164.08	2131.26	2126.88	2082.03
R.n	0.014	0.018	0.091	0.151	0.173	0.176	0.206
Chi Square	19	24	121	205	238	242	287
Degrees of Freedom	2	4	5	21	24	27	30
p	9e-05	1e-04	0.000	0.000	0.000	0.000	0.000
Residual Deviance	1712	1710	1709	1693	1690	1687	1684
AIC	2357	2356	2260	2208	2181	2183	2144
Accuracy	52.7%	53.5%	61.7%	64.3%	64.2%	64.5%	65.3%

Table 3 provides the results from the final hierachical regression model (Model 7). Statistically significant positive trends (e.g. increase in the parameter increases success rates) were observed for 1) *Turbine Capacity*; 2) *Distance to Urban Regions*; 3) *Distance to AONB* 4) *Distance to National Parks* and 4) *Distance to Nearest Turbine (Rejected)*. Negative associations were found for 1) *Year*; 2) *Distance to Ramsar sites* 3) *Distance to Natura 2000 sites*; 4) *Qualifications L4 (University degree or above)*; 5) *Mean Age*; 6) *Nearest Turbine (Operational)*.

The total number of parameters retained in the parsimonious model was reduced to 15. This resulted in a marginal penalty in performance of the model, with the R^2 values reducing from 0.2 to 0.193. The odds ratios (OR) for these remaining parameters are shown for each parameter in Figure 7, whereby an OR = 1 means the parameter does not affect odds of the planning outcome, OR > 1 indicate the parameters positively influence planning acceptance, OR < 1 represents a negative parameter influence.

The results of the nationally-segmented models are summarised in Table 4, comparing the *Global Parameters* against *Optimised Parameters*. There has been a general increase in the fit of the models represented by the Nagelkirke R^2 values. The difference between Odds Ratios between each model is further highlighted in Figure 8.

Finally, the results of the statistical generalisation are presented in Figure 9. The average acceptance value of the model is 21.9%. Only 1.84% of sites were predicted to have a greater than 50% chance of success, and 10.9% of sites were predicted to have an acceptance rate of less than 10%.

5 Discussion

The overall model fit of parameters is comparatively low based on geospatial parameters alone with the global parsimonious model achieving a fit of 0.2. Compared to Van Rensburg et al. [52], an overall McFadden adjust R^2 value of 0.31 was determined. Although fewer geospatial parameters were included

Table 3: Odds Table for Logistic Regression Parameter

Variable	Estimate	Std. Error	z value	Pr	Sig.	Odds Ratio	OR 2.5% CI	OR 97.5% CI
Number of Turbines	0.002	0.006	0.406	0.685		1.002	0.991	1.014
Turbine Capacity MW	0.371	0.068	5.496	0.000	***	1.450	1.271	1.657
Wind Speed	-0.091	0.063	-1.448	0.148		0.913	0.807	1.033
Distance to HV Powerlines	0.002	0.009	0.244	0.807		1.002	0.985	1.021
Year	-0.119	0.014	-8.517	0.000	***	0.888	0.863	0.912
Distance to Airports	0.008	0.004	2.067	0.039	*	1.008	1.000	1.015
Distance to A Roads	0.003	0.013	0.247	0.805		1.003	0.979	1.028
Distance to B Roads	-0.033	0.019	-1.717	0.086	.	0.968	0.932	1.005
Distance to Minor Roads	0.050	0.071	0.702	0.482		1.051	0.915	1.207
Distance to Motorways	0.000	0.007	0.014	0.989		1.000	0.987	1.014
Distance to Railways	0.013	0.009	1.431	0.152		1.013	0.995	1.031
Distance to Urban Region	0.169	0.065	2.585	0.010	**	1.184	1.042	1.347
Distance to AONB	0.017	0.006	2.807	0.005	**	1.017	1.005	1.029
Distance to National Park	0.030	0.007	4.506	0.000	***	1.030	1.017	1.044
Distance to Heritage Coast	-0.010	0.009	-1.183	0.237		0.990	0.973	1.007
Distance to NNR	-0.004	0.007	-0.564	0.573		0.996	0.982	1.010
Distance to Ramsar	0.014	0.007	2.146	0.032	*	1.015	1.001	1.028
Distance to SACS	0.004	0.010	0.438	0.661		1.004	0.985	1.023
Distance to Natura 2000	-0.019	0.008	-2.306	0.021	*	0.981	0.965	0.997
Distance to SSSI	0.040	0.025	1.601	0.109		1.041	0.991	1.094
Distance to Military Sites	0.001	0.008	0.084	0.933		1.001	0.985	1.016
Qualifications, L4	-0.032	0.007	-4.596	0.000	***	0.968	0.955	0.981
Mean Age	-0.041	0.017	-2.367	0.018	*	0.960	0.928	0.993
Home Ownership	0.000	0.000	0.542	0.588		1.000	0.999	1.001
Political, Conservative Share	-0.001	0.003	-0.305	0.760		0.999	0.992	1.006
Political, Labour Share	0.005	0.004	1.279	0.201		1.005	0.997	1.013
Political, Liberal Democrat	0.003	0.005	0.694	0.488		1.003	0.994	1.013
Nearest Turbine (Operational)	-0.017	0.004	-4.238	0.000	***	0.983	0.975	0.991
Nearest Turbine (Rejected)	0.021	0.003	6.339	0.000	***	1.021	1.015	1.028
Distance to Large Urban Areas	-0.004	0.013	-0.316	0.752		0.996	0.971	1.022

Table 4: Comparison of subset Logistic Regression Models based on the global parameters list

		Global Parameter			Optimised Parameters		
	Global	England	Scotland	Wales	England	Scotland	Wales
Observations	1715	772	787	156	772	787	156
Parameters	16	16	16	16	10	13	9
Deviance	2093.74	926.83	940.35	176.02	931.5	942.86	179.88
R.n	0.198	0.209	0.232	0.302	0.202	0.228	0.276
Chi Square	275	131	150	40	126	148	36
Degrees of Freedom	15	15	15	15	9	12	8
p	0.000	0.000	0.000	0.00045	0.000	0.000	2e-05
Residual Deviance	1699	756	771	140	762	774	147
Accuracy	66.6%	66.3%	67.4%	60.3%	67.5%	67.2%	63.6%

within the former analysis, the study integrated greater institutional details and planning details.

5.1 Significant Parameters

For project characteristics, the size of the turbine capacity is indicated as a significant parameter, with larger turbines increasing the chance of acceptance. This at first appears counter intuitive, but may

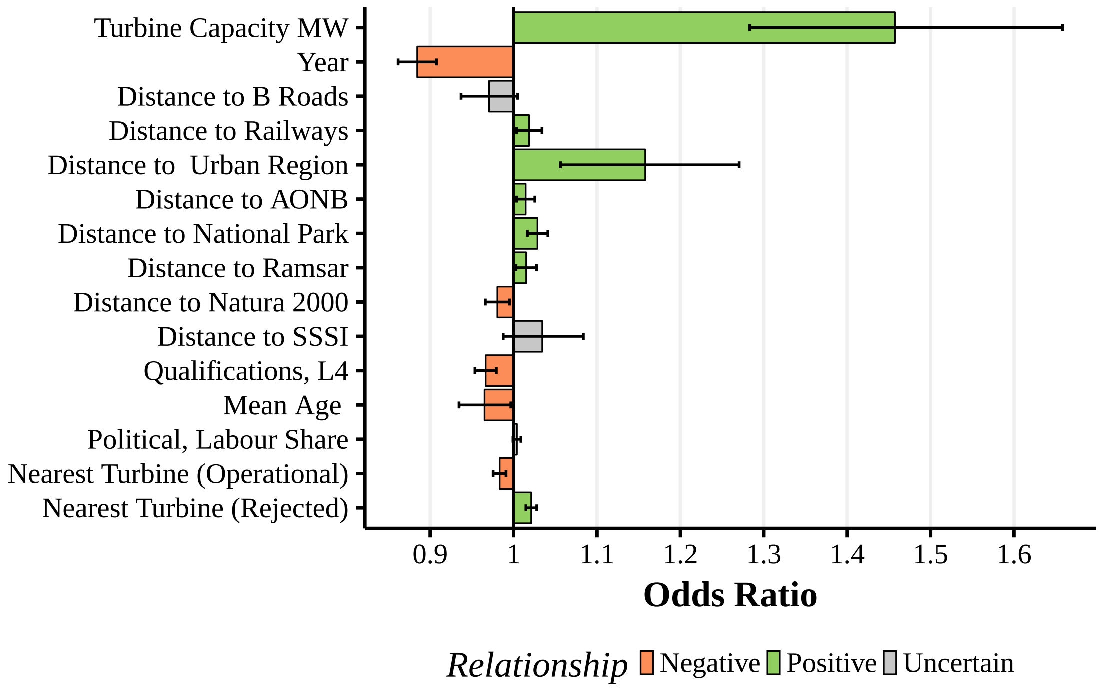

Figure 7: Odds Plot for Parsimonious Logistic Regression Model

suggest that the developers of bigger turbines are more likely to appeal the decisions made against larger wind farms, as rejection of such projects would result in a large loss of potential revenue. However, it should be noted that this variable has a small standard deviation (sd = 1.0) compared to other variables included within this model, and therefore the odds ratio inflates their influence within the model.

The distance to urban areas was indicated to be statistically significant, although there is considerable uncertainty as indiciated by the confidence interval. There are a number of potential causes for this: firstly, it could indicate that high wind speed sites suitable for development tend to be naturally less populated (i.e. hilly, isolated regions). Additionally, it may reflect a so-called “Not in My Back Yard” (NIMBY) view from the vocal local population, with projects in closer proximity to urban areas being more likely to be rejected. This has been a relatively contentious subject within literature, with a range of studies supporting [51,66] and rejecting [46,48,52] the NIMBY argument. However this study provides quantitative evidence to suggest that that sites closer to urban areas have a lower chance of acceptance.

For landscape and environmental designations, distance to National Parks, Ramsar and AONB were indicated as significant parameters although have marginal impacts. This potentially reflects the negative visual impacts which are often cited as a major impact of wind energy developments [5,66]. However, it should be noted that these influences have a relatively low impact, despite literature indicating that

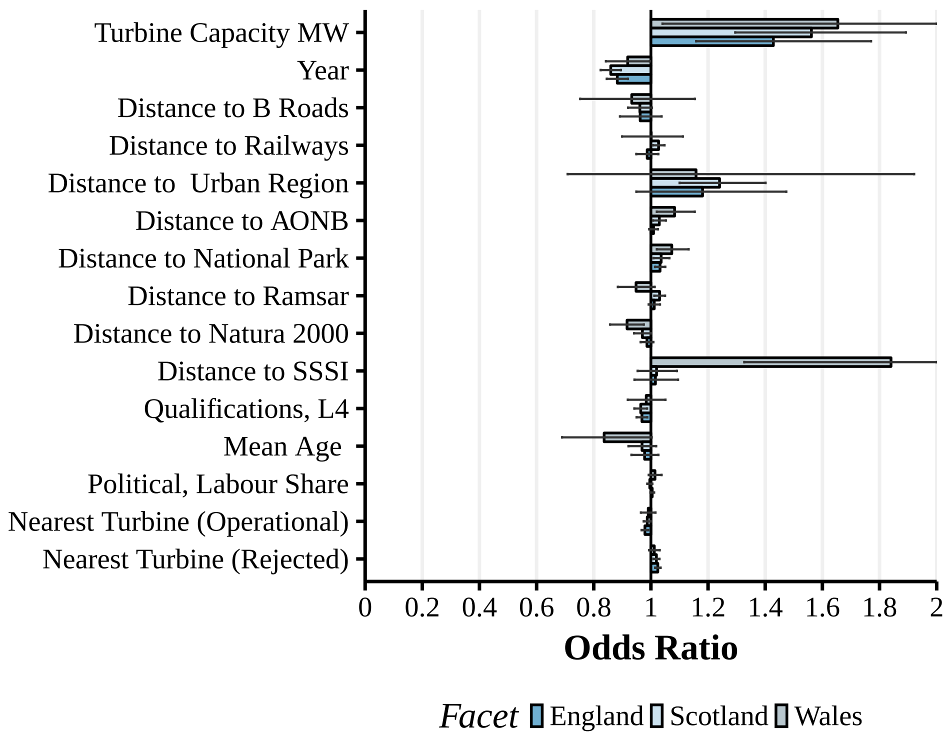

Figure 8: Odds plot for the nested logistic regression models for England, Scotland and Wales. Error bars indicate 95% confidence intervals.

landscape designations would play a more important role.

The level of qualifications, and the mean age of the local populous have been retained as significant parameters for demographic variables. It is suggested that regions of higher education may be more effective in organising campaign groups against such projects. This supports the hypothesis developed by Van der Horst and Toke [27] that developers were that developments are likely to avoid more privileged areas. To the author's knowledge, such a connection between acceptance rates and demographics has not be previously quantitatively validated.

The analysis suggests that proximity to existing wind energy developments may influence the likelihood of projects receiving planning. The nearest operational wind energy project was indicated as having a statistically significant negative effect, which suggests that projects further away from an existing project are less likely to be accepted. In addition, the nearest rejected project is suggested to be have a negative estimate, inferring that the further the site is from a previously rejected project, the higher the chance of acceptance. This "proximity hypothesis" has been a contentious subject challenged within literature [39–41]. However, this study provides quantitative evidence to challenge this view.

There are notable parameters which are frequently used in GIS modelling, but do not prove influential, including wind speed and the proximity to airports. This may reflect that these parameters represent

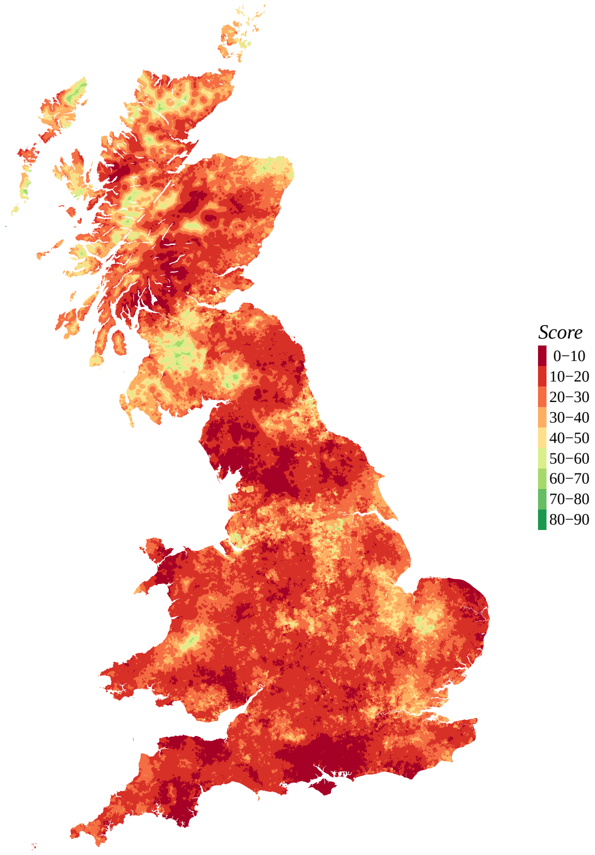

Figure 9: Predicted Raster of Site Acceptance

technical challenges which can be investigated in the early stages of project development, and therefore any sites that are not suitable will not seek planning permission.

5.2 National Models

The split data model developed suggests that despite hypthosized differences between the three countries, there is limite variation between the significant influential parameters as shown in Figure 8. Only *Wind Speed* exhibited statistically significant variations influences, with the model suggesting that sites in England have a greater chance of acceptance. However, the reduced number of observations used to build each model increases the uncertainty substantially as indicated by the confidence intervals.

5.3 Generalisation

The national prediction raster shown in Figure 9 highlights that there are large regional variations within wind energy site acceptability. For example, large regions in Scotland appear suitable for development, while many other regions with the South of England appear “off limits” to development, particularly the regions along the South Coast of the UK.

For the overall model, there is a low average predicted acceptance rate of 21.9% which is below the rate of acceptance of wind energy in the UK, which was 40% in 2017 [6]. It would be expected that the model would return a lower average, as sites which are selected by developers will pass through several preselection criteria prior to planning permission [7]. Therefore, sites which are generally opposed before planning will often be abandoned before being taken to planning permission.

The analysis results suggest that there is no “one-size-fits-all” approach for spatial modelling, and that there are large regional variations in the development of wind energy projects beyond the availability of the resource. In comparison, the regional renewable energy studies conducted within the UK in 2010 broadly followed a consistent methodology to assess the resource potential, with small differences in the development rules in particular regard to environmental and landscape designations [67]. It is therefore important that geospatial modelling aims to integrate local understanding to more accurately capture this variation.

Surprisingly, the model suggests that the South West of England has a low likelihood of acceptance, despite having high levels of wind energy within the area. The UK’s wind energy development largely started in the region, so it had generally been considered supportive of wind energy [39]. Upon inspection

6 Conclusions & Policy Recommendations

This paper has investigated the influence of geospatial, environmental, demographic and political attributes on the probability of wind farm planning approval in Great Britain between 1990 and 2016. The study findings reveal that local demographic parameters appear to influence the planning outcomes of projects, and that many of the geospatial parameters typically integrated into wind turbine models appear insignificant in determining site approval. To the authors’ knowledge, such quantitative findings have not previously been demonstrated using such datasets.

UK energy policy has shifted towards a more hostile stance against onshore wind energy since 2015. In particular, the approval of planning has been granted to local communities. It appears that certain demographics are less accepting of onshore wind in Great Britain. Given that UK planning policy has now devolved power locally and allowing local communities to have the final say on projects [7], there may be a clear block to development in certain regions in the country.

In addition, the results raise concerns of the predictive ability of existing geospatial modelling in locating wind energy sites. These findings provide evidence to support existing literature that GIS tools in themselves are of limited applicability [26,47], and supports the conclusion that greater emphasis needs to be given to the non-physical elements of a project (e.g. Community engagement with the scheme from an early stage) [4,35,44].

Although the results have been calculated within the context of the UK, these findings are of interest internationally. There are opportunities for spatial plannings to acknowledge the demographic influence on wind energy development. It

In relation to future UK onshore wind, non-technical parameters (such as voter preference, social opinion) may change, and therefore the outcomes of these results may help inform the location of socially acceptable wind turbine sites.

It should be noted that the parameters used to derive these findings are obtained with context to Great Britain, and therefore may have limited applicability internationally, and therefore should be applied with caution outside of this region. There are opportunities to expand upon this work by exploring the international context of the finding to widen its applicability.

The generalised map highlight that there are regions in the UK which still appear

However, with the estimated cost of planning applications for commercial scale projects exceeding £50000 [68], there is large value in even marginal improvements in the site selection. The findings from this model can help inform regional level strategy and provide an insight to developers of where projects may be more suitable for future development

POLICY

- Uk transferred planning permission to local communities.

There is recent evidence that the UK government may be looking to soften the stance against onshore wind energy http://data.parliament.uk/writtenevidence/committeeevidence.svc/evidencedocument/business-energy-and-industrial-strategy-committee/clean-growth-strategy/oral/74989.html

Acknowledgments

This work is part of the activities of the Energy and Climate Change Division and the Sustainable Energy Research Group at the University of Southampton www.energy.soton.ac.uk. It is also supported by ESPRC under grant EP/J017698/1, Transforming the Engineering of Cities to Deliver Societal and Planetary Wellbeing and the Faculty of Engineering and Environment at the University of Southampton.

Supplementary Files

The analysis and report was written using the R programming language and RMarkdown [69]. The full statistical analysis and turbine dataset is provided with the supporting files available to recreate the results presented in this report.

A online appendix is provided which provides the full statistical analysis and diagnostic checks.

References

[1] UNEP, Global trends in renewable energy, (2016). https://goo.gl/0GtPT4 (accessed January 20, 2017).

[2] Department for Business Energy & Industry, Electricity Generation Costs, 2016.

[3] Europe's onshore and offshore wind energy potential, 2009. doi:10.2800/11373.

[4] M. Wolsink, Wind power and the NIMBY-myth: institutional capacity and the limited significance of public support, Renewable Energy. 21 (2000) 49–64. doi:10.1016/S0960-1481(99)00130-5.

[5] K. Langer, T. Decker, J. Roosen, K. Menrad, A qualitative analysis to understand the acceptance of wind energy in Bavaria, Renewable and Sustainable Energy Reviews. 64 (2016) 248–259. doi:10.1016/j.rser.2016.05.084.

[6] DECC, Renewable Energy Planing Data, (2016). https://www.gov.uk/government/collections/renewable-energy-planning-data (accessed April 25, 2016).

[7] L. Smith, Planning for onshore wind farms, House of Commons Briefing Paper. (2016). http://www.parliament.uk/briefing-papers/sn04370.pdf.

[8] D. Voivontas, D. Assimacopoulos, a. Mourelatos, J. Corominas, Evaluation of renewable energy potential using a GIS decision support system, Renewable Energy. 13 (1998) 333–344. doi:10.1016/S0960-1481(98)00006-8.

[9] S.M.J. Baban, T. Parry, Developing and applying a GIS-assisted approach to locating wind farms in the UK, Renewable Energy. 24 (2001) 59–71. doi:10.1016/S0960-1481(00)00169-5.

[10] H.S. Hansen, GIS-based Multi-Criteria Analysis of Wind Farm Development, Proceedings of the 10th Scandinavian Research Confrence on Geographical Information Scient. (2005) 75–87.

[11] C.D. Yue, S.S. Wang, GIS-based evaluation of multifarious local renewable energy sources: A case study of the Chigu area of southwestern Taiwan, Energy Policy. 34 (2006) 730–742.

doi:10.1016/j.enpol.2004.07.003.

[12] A.H.I. Lee, H.H. Chen, H.Y. Kang, Multi-criteria decision making on strategic selection of wind farms, Renewable Energy. 34 (2009) 120–126. doi:10.1016/j.renene.2008.04.013.

[13] J.R. Janke, Multicriteria GIS modeling of wind and solar farms in Colorado, Renewable Energy. 35 (2010) 2228–2234. http://people.umass.edu/bethanyb/Janke, 2010.pdf.

[14] SQW Energy, Renewable and Low-carbon Energy Capacity Methodology Methodology for the English Regions, 2010.

[15] N.Y. Aydin, E. Kentel, S. Duzgun, GIS-based environmental assessment of wind energy systems for spatial planning: A case study from Western Turkey, Renewable and Sustainable Energy Reviews. 14 (2010) 364–373. doi:10.1016/j.rser.2009.07.023.

[16] R. Van Haaren, V. Fthenakis, GIS-based wind farm site selection using spatial multi-criteria analysis (SMCA): Evaluating the case for New York State, Renewable and Sustainable Energy Reviews. 15 (2011) 3332–3340. doi:10.1016/j.rser.2011.04.010.

[17] B. Sliz-Szkliniarz, J. Vogt, GIS-based approach for the evaluation of wind energy potential: A case study for the Kujawsko-Pomorskie Voivodeship, Renewable and Sustainable Energy Reviews. 15 (2011) 1696–1707. doi:10.1016/j.rser.2010.11.045.

[18] V. Gass, J. Schmidt, F. Strauss, E. Schmid, Assessing the economic wind power potential in Austria, Energy Policy. 53 (2013) 323–330. doi:10.1016/j.enpol.2012.10.079.

[19] L. Neufville, Wind farm Site Suitability Selection using Multi-Criteria Analysis (MCA) and Spatial Modelling, (2013) 1–29.

[20] A. Miller, R. Li, A Geospatial Approach for Prioritizing Wind Farm Development in Northeast Nebraska, USA, ISPRS International Journal of Geo-Information. 3 (2014) 968–979. doi:10.3390/ijgi3030968.

[21] Q. Wang, M.M. M'Ikiugu, I. Kinoshita, A GIS-based approach in support of spatial planning for renewable energy: A case study of Fukushima, Japan, Sustainability (Switzerland). 6 (2014) 2087–2117. doi:10.3390/su6042087.

[22] J.J.W. Watson, M.D. Hudson, Regional Scale wind farm and solar farm suitability assessment using GIS-assisted multi-criteria evaluation, Landscape and Urban Planning. 138 (2015) 20–31. doi:10.1016/j.landurbplan.2015.02.001.

[23] Y. Noorollahi, H. Yousefi, M. Mohammadi, Multi-criteria decision support system for wind farm site selection using GIS, Sustainable Energy Technologies and Assessments. 13 (2015) 38–50.

doi:10.1016/j.seta.2015.11.007.

[24] K.B. Atici, A.B. Simsek, A. Ulucan, M.U. Tosun, A GIS-based Multiple Criteria Decision Analysis approach for wind power plant site selection, Utilities Policy. 37 (2015) 86–96. doi:10.1016/j.jup.2015.06.001.

[25] M. Baseer, S. Rehman, J. Meyer, M.M. Alam, GIS-based site suitability analysis for wind farm development in Saudi Arabia, Energy. (2017). doi:10.1016/j.energy.2017.10.016.

[26] J. Malczewski, GIS-based land-use suitability analysis: A critical overview, Progress in Planning. 62 (2004) 3–65. doi:10.1016/j.progress.2003.09.002.

[27] D. van der Horst, D. Toke, Exploring the landscape of wind farm developments; local area characteristics and planning process outcomes in rural England, Land Use Policy. 27 (2010) 214–221. doi:10.1016/j.landusepol.2009.05.006.

[28] J. Cirucci, Retrospective GIS-Based Multi-Criteria Decision Analysis, (2014).

[29] J.G. Brody, D.J. Vorhees, S.J. Melly, S.R. Swedis, P.J. Drivas, R.A. Rudel, Using GIS and historical records to reconstruct residential exposure to large-scale pesticide application, Journal of Exposure Analysis and Environmental Epidemiology. 12 (2002) 64–80. doi:10.1038/sj/jea/7500205.

[30] N.S. Mohamed, L.M. Nofal, M.H.A. Hassan, S.M. Elkaffas, Geographic information systems (GIS) analysis of under five mortality in Alexandria., The Journal of the Egyptian Public Health Association. 79 (2004) 243–262.

[31] I. Yamada, P.A. Rogerson, G. Lee, GeoSurveillance: A GIS-based system for the detection and monitoring of spatial clusters, Journal of Geographical Systems. 11 (2009) 155–173. doi:10.1007/s10109-009-0080-1.

[32] S. Garcia-Ayllon, Retrospective analysis of urban development in the Spanish Mediterranean coast, WIT Transactions on Ecology and the Environment. 179 VOLUME (2013) 291–302. doi:10.2495/SC130251.

[33] O.O. of R.C. US EPA, Recovery, Waste Transfer Stations: A Manual for Decision-Making, (2002) 1–66. papers3://publication/uuid/7CAEDFA2-1B14-4CFF-8B13-1E920D35AD80.

[34] J.F. Cirucci, D.A. Miller, J.I. Blanford, Retrospective GIS-Based Multi-Criteria Decision Analysis: A Case Study of California Waste Transfer Station Siting Decisions, Proceedings of the International Symposium on Sustainable Systems and Technologies. 3 (2015). doi:10.6084/m9.figshare.1512514.

[35] D. Toke, S. Breukers, M. Wolsink, Wind power deployment outcomes: How can we account for the differences?, Renewable and Sustainable Energy Reviews. 12 (2008) 1129–1147.

doi:10.1016/j.rser.2006.10.021.

[36] P. Devine-Wright, Local aspects of UK renewable energy development: exploring public beliefs and policy implications, Local Environment. 10 (2005) 57–69. doi:10.1080/1354983042000309315.

[37] 'Green On Green': Public perceptions of wind power in Scotland and Ireland, Journal of Environmental Planning and Management. 48 (2005) 853–875. doi:10.1080/09640560500294376.

[38] S. Krohn, S. Damborg, On Public Attitudes Towards Wind Power, Renewable Energy. 16 (1999) 954–960. doi:10.1016/S0960-1481(98)00339-5.

[39] D.C. Eltham, G.P. Harrison, S.J. Allen, Change in public attitudes towards a Cornish wind farm: Implications for planning, Energy Policy. 36 (2008) 23–33. doi:10.1016/j.enpol.2007.09.010.

[40] J. Meyerhoff, C. Ohl, V. Hartje, Landscape externalities from onshore wind power, Energy Policy. 38 (2010) 82–92. doi:10.1016/j.enpol.2009.08.055.

[41] J. Ladenburg, A. Dubgaard, Willingness To Pay For Reduced Visual Disamenities From Off-Shore Wind Farms In Denmark BT - Third World Congress Of Environmental And Resource Economists, (2006).

[42] P.a. Strachan, D. Lal, Wind energy policy, planning and management practice in the UK: Hot air or a gathering storm?, Regional Studies. 38 (2004) 551–571. doi:10.1080/0143116042000229311.

[43] C.R. Jones, B.J. Orr, J.R. Eiser, When is enough, enough? Identifying predictors of capacity estimates for onshore wind-power development in a region of the UK, Energy Policy. 39 (2011) 4563–4577. doi:10.1016/j.enpol.2011.04.044.

[44] C.R. Warren, M. McFadyen, Does community ownership affect public attitudes to wind energy? A case study from south-west Scotland, Land Use Policy. 27 (2010) 204–213. doi:10.1016/j.landusepol.2008.12.010.

[45] P. Devine-Wright, Reconsidering public attitudes and public acceptance of renewable energy technologies : a critical review, Architecture. Working Pa (2007) 1–15. goo.gl/wdj68L.

[46] Populus, Energy Balance of Power Poll Fieldwork : July 1st-6th 2005, (2005) 1–23.

[47] D. Toke, Explaining wind power planning outcomes: Some findings from a study in England and Wales, Energy Policy. 33 (2005) 1527–1539. doi:10.1016/j.enpol.2004.01.009.

[48] P. Devine-Wright, Beyond NIMBYism: Towards an integrated framework for understanding public perceptions of wind energy, Wind Energy. 8 (2005) 125–139. doi:10.1002/we.124.

[49] R. Wustenhagen, M. Wolsink, M.J. Burer, Social acceptance of renewable energy innovation: An introduction to the concept, Energy Policy. 35 (2007) 2683–2691. doi:10.1016/j.enpol.2006.12.001.

[50] M. Sonnberger, M. Ruddat, Local and socio-political acceptance of wind farms in Germany, Technology

in Society. 51 (2017) 56–65. doi:10.1016/j.techsoc.2017.07.005.

[51] C. Haggett, D. Toke, Crossing the great divide-using multi-method analysis to understand opposition to windfarms, Public Administration. 84 (2006) 103–120. doi:10.1111/j.0033-3298.2006.00495.x.

[52] T.M. van Rensburg, H. Kelley, N. Jeserich, What influences the probability of wind farm planning approval: Evidence from Ireland, Ecological Economics. 111 (2015) 12–22. doi:10.1016/j.ecolecon.2014.12.012.

[53] HM Government, Planning Portal Northern Ireland, (2014).

[54] DTI, NOABL Windspeed Database, (2001). https://goo.gl/6BALyv (accessed October 21, 2016).

[55] Ordnance Survey, OS Strategi, (2016). https://data.gov.uk/dataset/strategi.

[56] OSM, Overpass API, (2016). https://overpass-turbo.eu/.

[57] A. Pope, UK National Parks, (2017). http://dx.doi.org/10.7488/ds/1810.

[58] European Commission, Digital Elevation Model over Europe (EU-DEM), (2015). http://www.eea.europa.eu/data-and-maps/data/eu-dem{\#}tab-european-data (accessed November 20, 2016).

[59] M.D. Fleming, R.M. Hoffer, Machine Processing of Landsat MSS Data and DMA Topographic Data for Forest Cover Type Mapping, LARS Technical Report 082879 Laboratory for Applications of Remote Sensing, Purdue University, West Lafayette, Indiana. (1979) 377–390.

[60] Office for National Statistics, 2011 Census data, (2016). https://www.ons.gov.uk/census/2011census/2011censusdata (accessed October 20, 2016).

[61] B. Gove, R. Langston, A. McCluskie, J. Pullan, I. Scrase, Wind farms and birds: an updated analysis of the effects of wind farms on bird, and best practice guidance on integrated planning and impact assessement, 2013.

[62] F.E. Harrell, Regression modeling strategies. With applications to linear models, logistic regression, and survival analysis, 2001. doi:10.1007/978-1-4757-3462-1.

[63] ONS, 2011 Census, Quick Statistics for Wales on National Identity, Passports Held and Country of Birth, (2013).

[64] J.C. Stoltzfus, Logistic regression: A brief primer, Academic Emergency Medicine. 18 (2011) 1099–1104. doi:10.1111/j.1553-2712.2011.01185.x.

[65] M.D. Ward, Spatial Regression Models, 2008.

[66] C.R. Jones, J. Richard Eiser, Understanding 'local' opposition to wind development in the UK: How

big is a backyard?, Energy Policy. 38 (2010) 3106–3117. doi:10.1016/j.enpol.2010.01.051.

[67] H. Stoddart, D. Turley, Review of approaches adopted in regional renewable energy capacity assessments when following the Regional Renewable and Low Carbon Energy Capacity Methodology, 2012.

[68] Renewables First, Wind Turbine Planning Permission, (2016). http://www.renewablesfirst.co.uk/windpower/wind-turbine-consenting/wind-turbine-planning-permission/ (accessed September 2, 2017).

[69] J. Allaire, Y. Xie, J. McPherson, J. Luraschi, K. Ushey, A. Atkins, H. Wickham, J. Cheng, W. Chang, Rmarkdown: Dynamic documents for r, 2018. https://CRAN.R-project.org/package=rmarkdown.

[70] P. Scherhaufer, S. Höltinger, B. Salak, T. Schauppenlehner, J. Schmidt, Patterns of acceptance and non-acceptance within energy landscapes: Acase study on wind energy expansion in Austria, Energy Policy. 109 (2017) 863–870. doi:10.1016/j.enpol.2017.05.057.

Add reference: [70]

Appendix

Table 5: Summary of data sources used within model

ID	Category	Variable	Source	Data Type	Variable Value	Value Type	Unit
1	Turbine	Wind Turbine Planning Data	REPD	Tabular	Planning Outcome	Categorical	Accept/Reject
2		Turbine Capacity		Tabular	Megawatts/turbine	Continuous	MW
3		Number of Turbines		Tabular		Continuous	
4		Year		Tabular		Discrete	
5		Country		Tabular		Categorical	
6	Resource	Wind Speed	NOABL	Raster	Annualised Wind Speed	Continuous	m/s
7	Features	Airports	OpenGeo	Points	Distance to Feature	Continuous	km
8		Roads[a]	OS Strategi	Lines	Distance to Feature	Continuous	km
9		Railways		Lines	Distance to Feature	Continuous	km
10		Urban Areas		Polygons	Distance to Feature	Continuous	km
11		HV Powerlines[b]	OSM	Lines	Distance to Feature	Continuous	km
12		Military Sites	OSM	Points, Polygons	Distance to Feature	Continuous	km
13	Landscape	Areas of Outstanding Natural Beauty	National Heritage	Polygons	Distance to Feature	Continuous	km
14		National Parks		Polygons	Distance to Feature	Continuous	km
15		Heritage Coast		Polygons	Distance to Feature	Continuous	km
16	Nature	Special Protection Areas		Polygons	Distance to Feature	Continuous	km
17		National Nature Reserve		Polygons	Distance to Feature	Continuous	km
18		Sites of Special Scientific Interest		Polygons	Distance to Feature	Continuous	km
19		Special Areas of Conservation		Polygons	Distance to Feature	Continuous	km
20	Geographic	Elevation	EU DEM	Raster	Height above sea level	Integer	m
21		Slope	Derived from 18	Raster	Gradient	Continuous	%
22	Census	Level of Qualification[c]	ONS	Tabular	Higher than L4	Continuous	%
23		Age		Tabular	Mean	Continuous	Years
24		Social Grade[d]		Tabular	Social Grade AB	Continuous	%
25		Tenure		Tabular	Home Ownership	Continuous	%
26	Political	Conservatives	Populus	Tabular	Percentage of Council	Continuous	%
27		Labour		Tabular	Percentage of Council	Continuous	%
28		Liberal Democrat		Tabular	Percentage of Council	Continuous	%
29	Proximity	Nearest Turbine (Operational)	Calculated	Points	Distance to Turbine	Continuous	km
30		Nearest Turbine (Rejected)	Calculated	Points	Distance to Turbine	Continuous	km

[a] Roads are broken into four main categories: Motorways, A Roads, B Roads and Minor Roads
[b] High Voltage network at 140 400kV
[c] L4 represents degree level or above
[d] AB represents Higher and intermediate managerial, administrative, professional occupation