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Spatial planning scale for regional renewable energy supply in the UK context

by

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ABSTRACT

FACULTY OF ENGINEERING AND THE ENVIRONMENT
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Doctor of Philosophy

SPATIAL PLANNING SCALE FOR REGIONAL RENEWABLE ENERGY SUPPLY IN THE UK CONTEXT

by Michael Harper

Faced with challenges of energy security and recognition of the anthropogenic climate change, there have been ongoing international efforts to develop indigenous renewable energy resources. This transition is challenging traditional planning approaches of energy systems, with difficulties faced in both identifying suitable locations for renewable energy development, and issues in delivering projects within existing top-down governmental planning structures.

Within the context of the United Kingdom, this project explored the vulnerability of cities and regions in meeting their electricity requirements through renewable energy sources. Onshore wind energy was selected as the primary focus of the study, being the most established technology in the region, with over 3000 planning applications made between 1990 and 2017.

In order to create a more accurate site location model, analysis was conducted to identify the influential factors for a wind energy site receiving planning permission. This understanding was then integrated into a novel onshore wind site selection model, assessing the economic, legislative and social suitability of potential wind energy site. Finally, an overarching methodology to assess the potential for a region to meet its energy requirements through renewable energy resources was proposed, with the methodology demonstrated within a case study which considered 14 UK towns and cities.

The study revealed that local demographic and political parameters appear to influence the planning outcomes of onshore wind energy projects. By integrating social constraints, the results from this onshore wind energy site modelling highlight that the exploitable wind capacity is an order of magnitude less than previous estimates. Finally, it is demonstrated that cities and regions face major restrictions in meeting their energy requirements through local renewable energy resources, and that there is the potential for resource conflict between neighbouring cities. The application of these findings can help inform planning policy and aid further renewable energy development within the United Kingdom.

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Declaration of Authorship

I, Michael Harper, declare that this thesis entitled Spatial planning scale for regional renewable energy supply in the UK context and the work presented in it are my own and has been generated by me as the result of my own original research.

I confirm that:

1. This work was done wholly or mainly while in candidature for a research degree at this University;
2. Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated;
3. Where I have consulted the published work of others, this is always clearly attributed;
4. Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work;
5. I have acknowledged all main sources of help;
6. Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself;
7. Either none of this work has been published before submission, or parts of this work have been published as: Harper et al. 2017.

Signed:

Date:

Acknowledgements

To the uninformed person[1], undertaking a PhD is often perceived as being an isolated experience, where you are locked in a lab or office for three years and avoid social interaction at all cost. Whilst this in part has been true, the support of others has been crucial to completion of the thesis and it is important to thank all those who have helped me throughout this ~~tortuous~~ challenging process.

Firstly, I would like to express my three supervisors who have helped me throughout the three years. Professor ‘Bakr Bahaj helped secured funding for the research project, and was pivotal in shaping the overall scope of the works. His years of experience and knowledge have always helped challenge my understanding of my research topic, and has reminded me of the importance in considering the direct impact that my research may have on real-world challenges.

I was fortunate enough to first work with my second supervisor, Professor Patrick James, during my Master’s Dissertation, and he opened my eyes to how much fun research could be. He has an incredible ability to provide insightful comments and feedback, and has helped drive progress in my work throughout the entire research project. Whilst his hectic timetable may make it difficult at times to schedule a meeting with, he always finds found time to help, even if it means sacrificing his evenings and weekends.

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Last but not least, I would like to thank my family for all their love and support. My parents have always encouraged me to pursue my interest in science and research. My brothers, Chris and Jonny, have always been there to talk and always help me take my mind off the work. Finally, my grandfather, Dr Glyn Court, was always an academic inspiration for me, and the opportunity to share the same title as him has provided vital motivation over much of the past year.

[1]This includes myself back in 2014

Acronyms

AHP	Analytic Hierarchy Procedure
AONB	Areas of Outstanding Natural Beauty
CCC	Climate Change Commission
CEA	Central Electricity Authority
CEB	Central Electricity Board
CEGB	Central Electricity and Gas Board
CHP	Community Heat and Power
DCLG	Department for Communities and Local Government
DECC	Department for Energy and Climate Change
DEM	Digital Elevation Model
DfT	Department for Transport
DoEN	Department for Energy
DUKES	Digest of United Kingdom Energy Statistics
DTI	Department of Trade and Industry
DZ	Data Zones
ECCC	Energy and Climate Change Committee
EfW	Energy from Waste
ELECTRE	Elimination and Choice Expressing Reality
ESCo	Energy Service Company
ETSU	Energy Technology Support Unit
ENSA	Energy Neutrality Scale Analysis
EPM	Energy Potential Mapping
GHG	Greenhouse Gases
GIS	Geospatial Information System
GWR	Geographically Weighted Regression
JNCC	Joint Nature Conservation Committee
LCOE	Levelised Cost of Electricity
LEP	Local Enterprise Partnership
LPA	Local Planning Authority
LEAP	Long-range Energy Alternatives Planning system
LSOA	Lower Super Output Area
MADA	Multi-attribute Decision Analysis
MCDA	Multi-criteria Decision Analysis

MODA	Multi-objective Decision Analysis
MOD	Ministry of Defence
NFFO	Non-Fossil Fuel Obligation
NIMBY	Not In My Back Yard
NNR	National Nature Reserve
NSIP	Nationally Significant Infrastructure Project
ONS	Office for National Statistics
OWA	Ordered Weighted Average
OS	Ordnance Survey
ONS	Office for National Statistics
POI	Points of Interest
PROMETHEE	Preference Ranking Organization Method for Enrichment Evaluations
RDA	Regional Development Agency
REPD	Renewable Energy Planning Database
RES	Renewable Energy Supply
ROC	Renewable Obligation Certificate
RSPB	Royal Society for the Protection of Birds
RSS	Regional Spatial Strategy
SAC	Special Area of Conservation
SDSS	Spatial Decision Support System
SPA	Special Protection Area
SSSI	Sites of Specific Scientific Interest
UNEP	United Nations Environment Programme
WSM	Weighted Sum Method
ZTV	Zone of Theoretical Visibility

Preface

This research was undertaken using the R programming language and is presented as an example of *reproducible research* and *literature programming*, whereby the analysis and written content are produced within a single workflow. Figures, results and statistical analysis are dynamically created within the report with the aim to make the work transparent and easily reproducible.

The printed version of this work does not display any project code, however a fully annotated version is available online through GitHub (github.com/mikey-harper/PhD) and will also be made available through the Pure online repository (`pure.soton.ac.uk`). The online repository also provides the full source code and access to datasets used within the analysis.

A number of other packages are used throughout the analysis. Those which provided a specific task within the analysis are referenced at their time of use, whilst the following packages are used throughout the analysis:

- **rmarkdown** (Allaire et al., 2017) **knitr** (Xie, 2017b) and **bookdown** (Xie, 2017a): used for producing the report within R.
- **ggplot** (Wickham & Chang, 2016): used for producing graphs and data visualisation.
- **ggmap** (Kahle & Wickham, 2017) is used for visualising spatial data.

In addition, the R package *sotonthesis* (Ismay & Harper, 2017) was developed by the author to produce the report in accordance with the University of Southampton thesis guidelines. Installation instructions are provided within the GitHub for reuse.

Session Information:

This thesis and analysis was built using R version 3.4.2 (2017-09-28) on the x86_64, linux-gnu operating system. The fully detailed system information is provided within the online repository. The code has been tested on both Linux and Windows systems and is stable at the time of publishing.

Chapter 1

Introduction

With a commitment to tackle climate change, the UK government established legally binding targets to reduce greenhouse gas emissions by a minimum of 80% by 2050 (*The Climate Change Act 2008*). Since the formation of these emission targets, significant investment has been made into renewable and low-carbon technologies, resulting in 25% of UK electricity being supplied by such sources in 2016 (DBIES, 2016a). However, there are growing concerns that the UK is not meeting the required rate of development in this sector, and it is projected that the UK will miss interim targets set for 2020 (ECCC, 2016).

To assist in the planning of renewable energy technologies, there has been significant international interest in methodologies to locate suitable sites for development. However, there are concerns within literature that existing approaches do not accurately model the social challenges surrounding the development of renewable energy projects (Langer et al., 2016). In particular, projects often face strong local opposition and experience difficulty in receiving planning permission, an issue which is particularly apparent within the UK, where over 50% of onshore wind energy projects are not granted planning permission (DECC, 2016c). Such high rejection rates have limited the capacity of the UK to meet renewable energy targets, and suggest potential under-performance of pre-planning methodologies in their assessments.

Furthermore, the decentralisation of energy in the UK has raised questions surrounding the scale at which energy systems should be planned. Historically, energy systems were largely coordinated at a regional or national scale, but there have been greater calls for devolution of control to cities and regions, who argue they are in a better position to deliver the development required for a low-carbon energy transition (Bridge et al., 2013). However, there is a limited understanding within existing literature of the optimal scale at which planning should be conducted within a low-carbon energy system, or how sub-national carbon targets should be set. This research therefore investigates the influence of spatial scale on the ability of a district to supply itself with sustainable energy generated within the boundaries of that district, termed "*energy neutrality*" (Jablonska et al., 2011). In doing so, this work seeks to contribute to the understanding of spatial scale in energy planning by providing quantitative evidence that builds upon existing qualitative literature.

In addition, this study assesses previous onshore wind energy planning decisions in the UK to determine the key parameters influencing the likelihood of a project receiving planning permission. Findings from this analysis are then integrated with technical and environmental constraints to identify suitable areas for development of onshore wind energy.

1.1 Research aims and objectives

Aims

The overall aim is to investigate the impact of spatial planning scale on the ability of a region to achieve energy neutrality. Within this scope, the study will identify factors that may influence the planning acceptance of onshore wind energy, and integrate the resulting information into spatial modelling of onshore wind energy to identify suitable locations for development.

Objectives

- To understand and assess the influence of technical, demographic and political parameters on the acceptance of onshore wind projects within a UK context.
- To develop a predictive model of the planning application acceptance of onshore wind energy based on the understanding achieved with the first objective.
- To assess the suitability of sites for onshore wind development, integrating the likelihood of the project receiving planning permission.
- To assess the impact of spatial planning scale on the ability of a region to achieve energy neutrality, using onshore wind as a case study.
- To develop a generalised approach for assessing the potential for energy neutrality of a region.
- To provide recommendations on the implication of the model results on regional energy planning.

1.2 Thesis Structure

For the purpose of clarity, the thesis was split into three parts, as follows:

- **Part I: Background & Literature**: aims to provide the overall context of the work conducted, and to provide justification for the research questions addressed.
- **Part II: Data Preparation**: explains the processes used to gather, validate and summarise datasets used within the modelling.
- **Part III: Analysis & Discussion**: details the modelling conducted and discusses the implications of the findings.

This structure is shown in Figure 1.1, providing a high-level summary of the key themes and development within the thesis. The map aims to highlight the connections between sections, and highlight the stages at which the project scope is refined throughout the document.

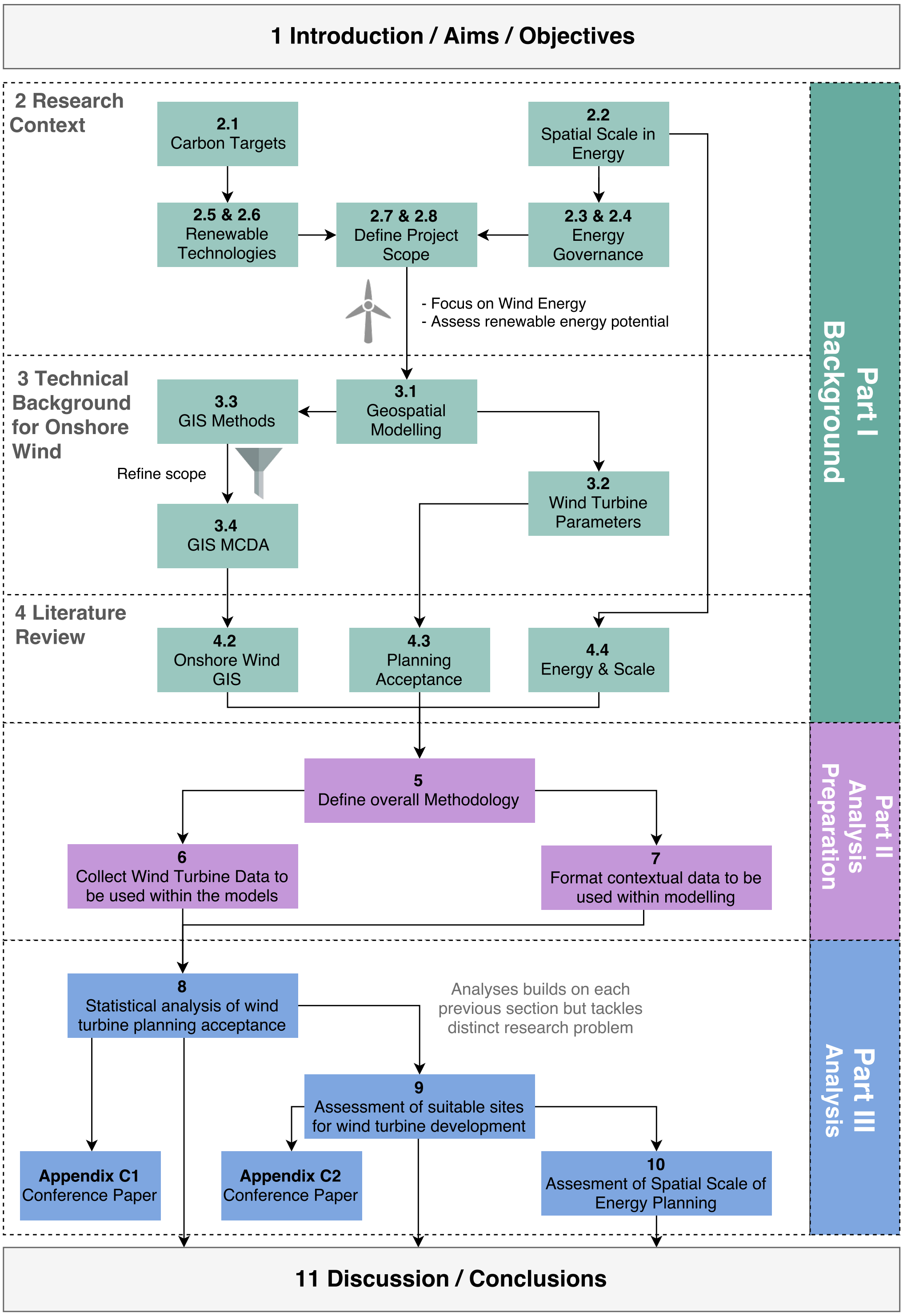
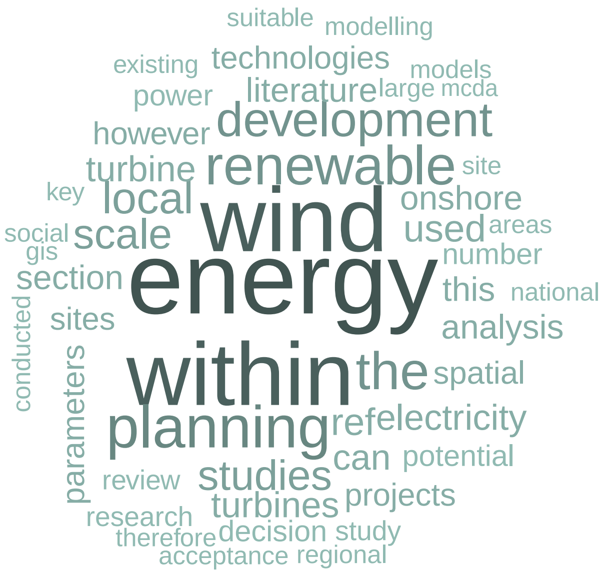


Figure 1.1: Thesis map highlighting the overall structure of the project.

Part I

Background & Literature



The aim of this section is to describe the overall context in which the work was conducted, and provide justification for the research questions developed. It is formed of the following chapters:

- **Chapter 2** provides the broader context of the work, highlighting the background challenges crucial to the development of the research topic.
- **Chapter 3** expands upon the issues framed within the background literature provided in Chapter 2, and details relevant technical concepts utilised within the research field.
- **Chapter 4** reviews the relevant academic literature, and highlights a number of limitations within existing approaches.

Chapter 2

Research Context

There are many legislative, technological and political issues surrounding the development of renewable energy technologies within the UK, and spatial scale forms a key component of this context. This chapter therefore aims to detail the key background information to help synthesize the research questions. Relating specifically to a UK context, the objectives of this chapter are as follows:

- to outline the legislative drivers and targets for the reduction of greenhouse gas emissions.
- to define the concept of spatial scale and its use within this project.
- to explain the importance of spatial planning scale within the transition to renewable energy technologies.
- to detail the historical development of the electricity network, highlighting the varying scales at which energy has been planned.
- to explore the recent trends in local government involvement within energy planning.
- to outline the renewable energy technologies within the UK context and summarise their suitability for further exploitation.
- to highlight spatial renewable energy capacity assessments conducted within government studies.
- to outline the challenges caused by the increased use of renewable energy technologies.
- to reflect upon the information presented and define the project scope for further assessment.

This chapter presents the broader context of renewable energy as a whole. The findings from this chapter are used to define the project scope, as explained within Section 2.8.1.

2.1 Drivers for Renewable Energy

The recognition of anthropogenic climate change has led to significant international action to reduce greenhouse gases (GHG) emissions. To this end, the UK government signed the Kyoto protocol to the UN Framework Convention on Climate Change in 1997 (United Nations, 1998), in the first legislative action to directly target emission reductions.

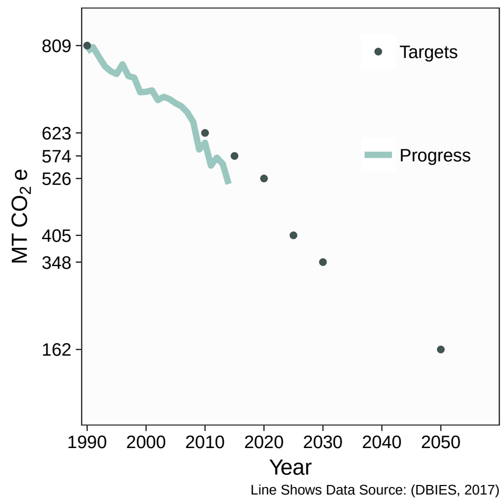
Long-term targets for the year 2050 were established through the Energy Paper 2003 (DTI, 2003). The recommendations of this report were legislated under the Climate Change Act 2008, which established legally binding targets to reduce carbon emissions by 80% between 1990 and 2050 ("Climate Change Act 2008," 2008). With electricity generation, transport and heating accounting for more than 80% of emissions[1], the development of renewable and low-carbon energy technologies is a critical aspect of meeting these targets.

To ensure regular progress towards the 2050 target, the Climate Change Act 2008 established a system of five-yearly carbon budgets proposed by the UK's Committee on Climate Change (CCC). In July 2016, the fifth carbon budget was set for the period 2028 to 2032 and requires a 57% reduction in emissions. Progress against the UK annual GHG emission targets are shown in Figure 2.1a, which highlights that that there has already been a 30% reduction between 1990 and 2013 (DBIES, 2016c). Whilst a significant portion of this reduction can be accounted for by renewable energy generation, a large part of the carbon reduction was achieved through fuel switching from coal to gas, the closure of many energy intensive industries,[2] and the prolonged recession of 2008 impacting economic activity (Griffin et al., 2013, 2016). Because of such one-off changes, it has become progressively more difficult to reduce emissions without the further exploitation of renewable energy technologies.

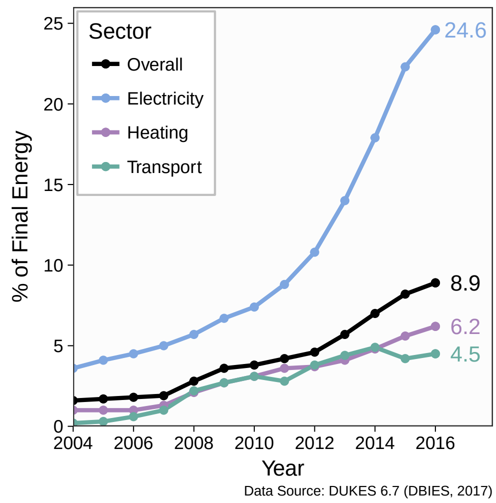
In addition to the carbon emission targets, the UK has a target of supplying 15% of overall energy consumption from renewable electricity by 2020 (European Parliament, 2009). Figure 2.1b shows the annual percentage of energy demand within the UK met by renewable sources. It can be seen that there has been significant growth in the supply of renewable energy over the past 10 years, and that 24.6% of electricity demand was met by renewable energy in 2016. However, the relatively slow progress in heating and transport has resulted in only 8.9% of overall energy demand being met by renewables. EU countries have also agreed to a new, non-legally binding, renewable energy target of 27% by 2030 (European Commission, 2014). This target highlights the need for the UK to ensure a consistent strategy to develop renewable energy and further reduce GHG emissions.

[1] Calculated from DUKES (DECC, 2016b)

[2] A notable example include the Redcar Steelworks (BBC, 2015)



(a) UK Annual Carbon Emissions. Megatonnes of carbon dioxide equivalent.



(b) Renewable energy as a percentage of final energy consumption in the UK, 2003 to 2015.

Figure 2.1: Graphs highlighting UK progress against emissions and carbon targets

Since the 2016 referendum on UK's membership of the EU, there have been further questions raised about the UK's commitment to renewable energy targets. As with all European led policy, it is unclear what policies will be retained if the UK leaves the EU. There are suggestions, however, that the renewable energy targets will be reduced or removed completely (Bloomberg, 2017). Despite this, the UK carbon emission targets have been set domestically and therefore emphasis remains on the commitment to reduce greenhouse gas emissions (DBIES, 2016a).

2.2 Spatial Scale

This section aims to frame the key definitions of spatial scale within energy modelling, and highlight the importance it plays within the development of energy modelling. The concepts outlined in this section are aimed to frame the issue of scale, and are expanded upon further within the chapter.

2.2.1 Concepts

The concept of spatial scale has multiple meanings, both between and within academic disciplines. Within the scope of this study, the *spatial data analysis* perspective is used, which relates to the scale at which the spatial measurement is conducted or planned (Lloyd, 2014). Although no strict definition is made of the different spatial scales, analyses often consider "local", "sub-regional", "regional", "national" and "global". Figure 2.2 expands upon these basic definitions by highlighting the administrative scales considered within energy planning and policy in the UK.

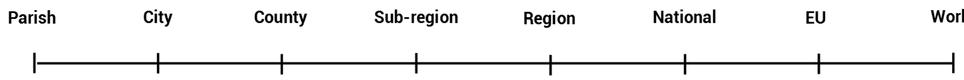


Figure 2.2: Schematic highlighting typical scales of planning within energy planning.

Electricity is an intrinsically spatial issue, with the production, distribution and consumption spanning multiple scales. As an example, Figure 2.3 outlines the typical arrangement of electricity distribution systems, with generation and demand occurring at remotely located power stations. In such an arrangement, electricity must be transmitted and distributed via regional electricity networks before being consumed at local areas. Such a structure has typically been led by regional and national scale planning, as explained further within Section 2.3.

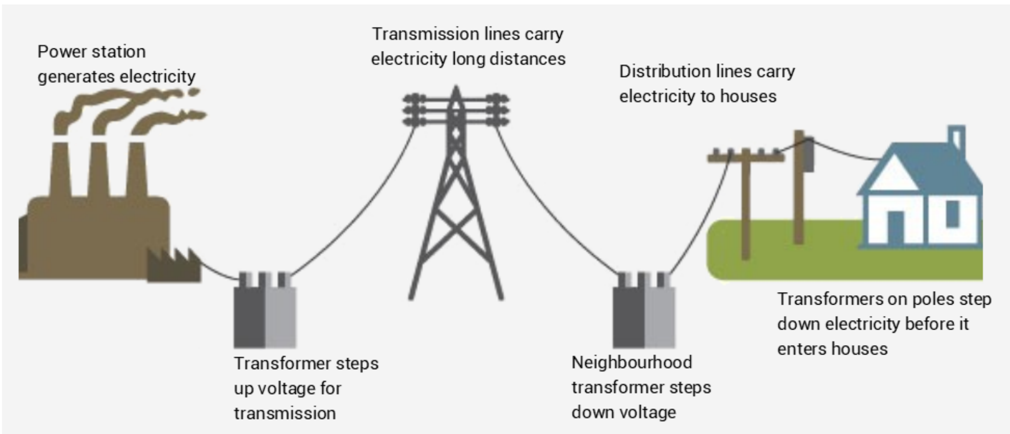


Figure 2.3: Schematic of electricity generation, transmission and distribution.

The traditional arrangement of electricity networks is being challenged within the energy transition to renewable and low-carbon technologies. Compared to traditional electricity systems, renewable technologies require significant local investment in decentralised technologies, and therefore action requires a much greater local perspective in planning (Ackermann et al., 2001). Increased interest within research has therefore been seen to assess the spatial dimension of sustainable transformations, with studies aiming to assess the geographical implication of a transition towards low carbon energy (Bridge et al., 2013; Bulkeley & Betsill, 2005; Spath & Rohracher, 2012).

2.2.2 Planning Scale and Energy

Scale forms an important aspect of planning. How social and political powers are organised and exercised over space is described as *territoriality* (Brenner et al., 2008). All infrastructure systems for energy capture, transmission and distribution are spatially constituted, but they have been territorialized in different ways over time: for example, initial electricity systems were developed as localised "islands" with no interconnection, however were replaced over time with integrated national scale energy systems.

Bridge et al. (2013, p. 10) note that "*the territorialisation of the UK energy system is an unsettled project that is on-going and contested*". In one aspect, the UK's energy system is being re-territorialised in the context of EU policies on the liberalisation of energy markets. At the same time, there is increasing recognition of the importance cities and urban infrastructural networks play in energy consumption, and therefore serve as a potentially important site for political action around energy transition (Bridge et al., 2013; Bulkeley & Betsill, 2005; Spath & Rohracher, 2012). These concepts are highlighted within Figure 2.4, and will be further explored within Sections 2.3 and 2.4.

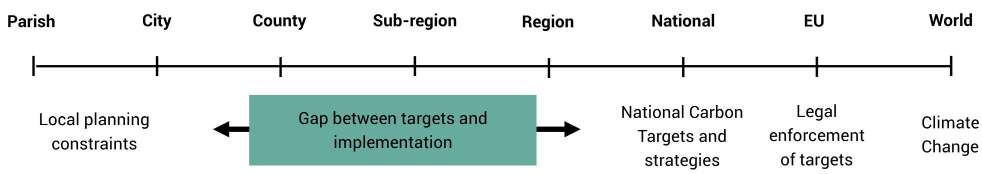


Figure 2.4: Schematic highlighting gap between planning and action within renewable energy development.

Despite concerns surrounding the importance of spatial scale, it has been noted that little significance has been placed on it within energy policy, and that assumptions about scale pervade existing decision-making. As noted Bridge et al. (2013), "*there is little questioning of the geographical imaginations which underpin the idea of nested and discrete scales of political authority over the environment*". This view reflects the limited understanding of the importance of spatial scale, and whether the existing structure of local, regional and national governments are the most suitable for the development of renewable energy technologies. Purcell (2006) further summarises:

> "It is dangerous to make any assumption about any scale. Scales are not independent entities with pre-given characteristics. Instead, they are socially constructed strategies

> to achieve particular ends. Therefore, any scale or scalar strategy can result in any outcome [...] All depends on the agenda of those empowered by a given scalar strategy."

In response to such concerns, it has been noted within governmental guidance that "*the scale of analysis should be tailored to mesh with functional issues and that different scales are appropriate for different issues*" (CLG, 2008, p. 69). This view largely mirrors the *Matching Principle*, whereby the scale of the infrastructure challenge should determine the appropriate governance level for responding to it (Butler & Macey, 1996). As shown, physical energy infrastructure exhibits a strong local dimension, and even regional, national or continental dimensions. Therefore, governmental arrangements should be established to account for the action required at the various spatial scales.

It is argued by the author that the existing government arrangements demonstrate a gap in knowledge (Figure 2.4). The lack of such integration can clearly be seen within national emission target planning in the UK, whereby national carbon targets have been set, yet there is limited coordination within the local scale investments required to meet such targets. This view is supported by literature that notes that there is often difficulty integrating spatial planning across multiple scales (Ran & Nedovic-Budic, 2016). These concerns are further explored within this chapter and the literature review in Chapter 4.

2.3 History of UK Energy and Governance

It was noted within Section 2.2 that the territorialisation of the UK electricity network has been a continuing project since its early development. To place recent trends within the broader social, political and technological landscape, it is important to understand the historical development of the electricity generation and distribution system within the UK. This section therefore provides a summary of the key developments that influenced current planning, and highlights the varying role that local governance has served. An overview of the timeline is provided in Figure 2.5, which is expanded upon within the following subsections.

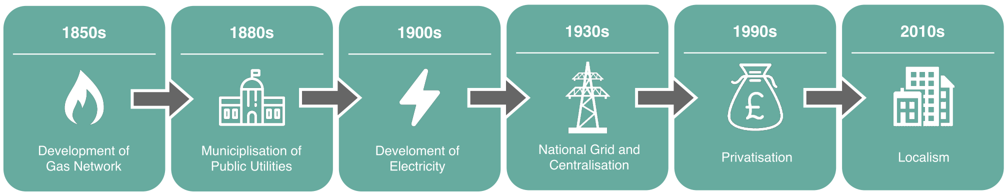


Figure 2.5: A timeline of UK electricity and the involvement of local government, 1850 to 2010.

2.3.1 1800s: Precursors of Electricity

In the early 1800s, the primary source of fuel for heating, power and cooking was coal, whilst all forms of artificial light were obtained from some form of open flame, either using candles or oil lamps. At this stage, there were no stand-alone lighting sources and none provided by a "*public utility*", a term generally referring to a company or organisation, either private or government-owned, that provides services to the general public over a network (Dupuit, 1844).

Developments in lighting had started at end of the 18th century, when it was discovered that gas could be derived from coal and burned in lanterns. While a small number of standalone gas lighting systems were built, the first public utilities devoted to illumination were gas networks within urban areas. These were developed from 1813, and by 1826, most towns of more than 10,000 people were served (Falkus, 1967). However, these early networks would initially serve to provide lighting for streets and commercial premises, with a limited number of domestic connections. It was not until the 1840s before it became affordable for domestic customers to be connected to the network (Falkus, 1982).

Up until 1850, there was very little involvement from local authorities in the operation of gas networks, and networks were primarily developed by private enterprises (Falkus, 1967). However, as local authorities sought to improve conditions for their local communities, there was increased interest in establishing and delivering public services and the concept of "*municipal socialism*" grew in importance, whereby local governments lead social reform (Cohn, 1910). A notable example is provided by Birmingham in 1873, whereby the council bought up local gas supplies and water networks to create large municipal networks (Ward, 2005). Following similar developments nationally, most cities and towns had control of their gas supply by the 1880s marking the beginning of involvement from local authorities that would last almost 70 years.

2.3.2 1880s: Early Developments of Electricity

The development of the electric utility had begun in earnest at the start of the 19th century. These steps included the scientific discovery of electricity, the creation of devices that used electricity (primarily lights and motors) and devising the means of transmitting and distributing electricity (Hausman et al., 2008). Like early gas systems, early electric generators had been sold as independent, self-dedicated units. Each system would have a generator that formed part of a complete system within itself. Such systems were installed throughout the 1860s and 1870s in the UK but were primarily limited to industrial customers (Hughes, 1983).

The first central electricity station in Britain opened in London in 1882, providing 160kW of power for lighting at Holborn Station and surrounding properties (Hughes, 1983). The Electric Lighting Act of 1882 allowed individuals, companies or local authorities to establish their own electricity supply systems. However, there was initially limited interest as such systems could cost from 3 to 8 times that of the old gas lighting (Byatt, 1962). In addition, municipal government had invested heavily in gas lighting and did not believe taxpayers' money should be invested in a technology that had not yet been proven. These issues led to an initially slow development of electricity networks, it would not be until the 1890s that widespread development began.

2.3.3 1890s: Electricity as a public utility

With technological improvements and increased acceptance of the value of electricity, public electricity systems began to be developed from the 1890s onwards. The first power stations were established in London in the years 1889-92 and in the early and mid-1890s electricity was supplied to the provinces. By 1900, the general trend was established that the large towns had municipal supply, while smaller towns had privately developed supplies (Byatt, 1962).

Most systems operated using a low voltage, and generally, it was uneconomical to supply areas greater than a half-mile radius due to the losses incurred with such systems. This limitation resulted in power plants being installed within urban areas, close to areas of demand. By the end of the First World War, such electrical networks had become well established within the UK. However, there was no standardised specification for such supplies, resulting in different AC and DC systems operating at a range of voltages and frequencies (Hughes, 1983). Reflecting upon this period, Hannah (1979) noted that *"there could be no doubt that a new strategy was required and that the existing structure of the industry was not conducive to the development of large central stations and bulk supply"*.

2.3.4 1924: The Weir Committee

To address the developing problems within the UK electricity infrastructure, the Weir Committee was established by the UK government in 1924 to provide recommendations for its improvement. The findings of their research were published in 1925, and outlined a number of changes which would reform the supply of electricity (The Weir Committee, 1926). The report recommended regional and national interconnections be formed through the construction of a 'gridiron'. The report also recommended the establishment of area boards that were coordinated under one central body, the Central Electricity Board (CEB). These changes marked a significant new direction in state enterprise which would foreshadow the subsequent trend of nationalisation within UK industries.

The concept of regional networks was well established by the 1920s, with countries such as the US and Germany establishing national grids within the 1910s (Chick, 2007). Hughes (1983, p. 356) summarised the design and operating principles of regional energy systems as follows:

- Obtaining economies of scale with large generating units (steam and water turbines).
- Massing the generating units near load centres or economical sources of energy and near cooling water (giant power plants).
- Transmitting electricity to load centres (high-voltage transmission lines).
- Cultivating mass consumption by charging low and differential rates and allowing supply to create demand.
- Interconnecting power plants to optimize their differential characteristics.
- Interconnecting loads to take advantage of diversity[3] and therefore raise load and demand factors.
- Centralising control of interconnected loads and power plants (establishing dispatching, or system-coordinating, centres).
- Forecasting load requirements in order to achieve optimum operations within the interconnect system
- Lowering installed and reserve capacity and coordinating maintenance shut downs through the exploitation of power plant interconnections.
- Accepting government regulation in order to establish a natural monopoly.
- Earning a regular and adequate return on investment in order to obtain capital at a reasonable interest rate.

2.3.5 1927: The National Grid

The Electricity Supply Act 1926 (HM Government, 1926) implemented the advice of the Weir Committee, establishing the CEB and commencing development of the National Grid. Construction started in 1927, and was the largest peacetime construction project that Britain had undertaken, with 3,000 miles of transmission lines and 28,000 pylons (Hughes, 1983).

[3]Diversity refers to having a mix of types of customers to reduce fluctuations in demand and avoidance of a common peak in demand

The construction of such a project was not without opposition. Many felt the creation of transmission pylons through rural areas disfigured the landscape and sought "the salvation of what is left of England's green and pleasant lands" (Anon., 1933).[4] It was noted that before the National Grid, the use of electricity had largely been confined to urban regions, with only 10% of the rural population having access to electricity in 1927 (CEB, 1929). Such environmental opposition for the electricity industry would resurface later in the century with the development of wind energy in the UK.

With the formation of the National Grid, the UK could begin to benefit from the economies of scale offered, resulting in a rapid increase in electricity demand: between 1926 and 1944, demand for electricity increased from 6TWh to 36TWh while the number of generating stations was reduced from approximately 600 to 362.[5]

2.3.6 1947: Centralisation and Nationalisation

From the early 1900s until 1947, local authorities had played an important role within the development of electricity networks. By 1947, 60% of electricity capacity was controlled by local authorities (Electricity Commission, 1948). However, there was a drive for nationalisation in UK industries to ensure a coordinated approach in future developments. To this effect, the Electricity Act 1947 (HM Government, 1947) nationalised the electricity generation and supply industry, consolidating the companies into 14 regional electricity boards of the new Central Electricity Authority (CEA). This removed the local municipality influence on energy supply and transferred powers to a regional and national level (Katzarov, 1964).

The period from 1947 until the 1970s experienced a surge in demand for electricity, and there was a consequent increase in the supply of electricity as shown in Figure 2.6. Up until the 1950s, coal had provided the bulk of this electricity generation, with only a single oil power plant at Bankside in London and nuclear power yet to contribute to electricity generation. However, it had become clear that demand for coal would not be met by the 1960s (Ashworth, 1986), prompting the government to begin the investigation into alternative sources. While the primary focus had been to explore nuclear and domestic oil production, the potential of wind power was briefly explored with an isolated attempt to construct a demonstration wind turbine in Wales in 1955 (CEGB, 1981). These plans were however overturned by intense opposition from the affected local community.

The restructuring of the electricity industry during the 1950s unintentionally coincided with the 1956 Suez Crisis, which impacted global oil supplies and highlighted the risk of security of supply. This period provides a useful insight into the beliefs of the future inputs for electricity generation. Chick (2007) suggests that there was an over-reaction by the UK with a massive expansion in the nuclear programme, and a planned shift within the UK energy mix away from coal. Energy security dominated the fuel choices of UK government, and nuclear energy was seen as a key part of this plan. Such a view would often come at the expense of renewable energy, as explained further in the following section.

[4] More example includes (Croft, 1932, Anon. (1932))

[5] These figures were calculated from the CEB Annual Electricity Reports (Electricity Commission, 1948, p. 17)

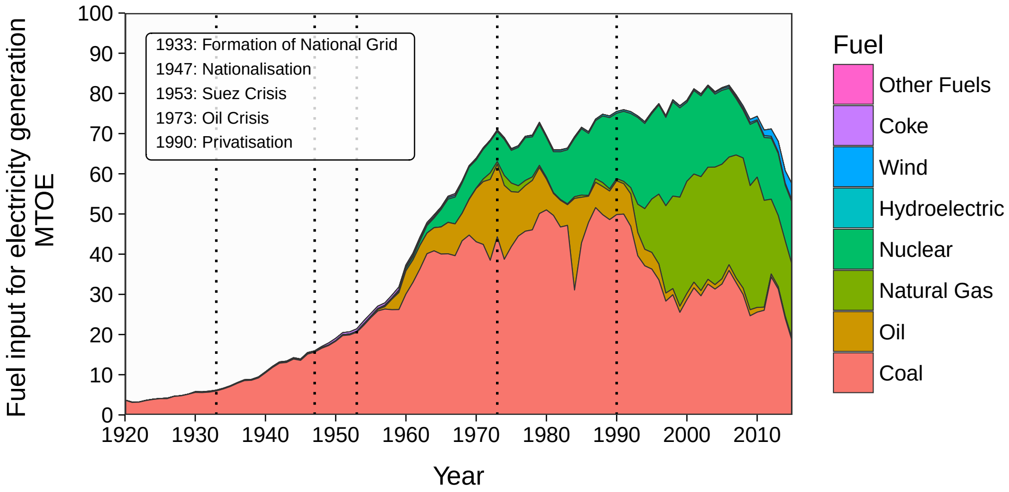


Figure 2.6: UK Fuel Input for electricity generation. Lines refer to key dates in UK energy development. Data Source: DUKES (DBIES, 2016).

2.3.7 1970s: Beginning of Renewable Energy Research

By the 1970s, oil had overtaken coal as the main source of fuel in the UK, accounting for nearly 48 percent of primary energy consumption (DBIES, 2016b).[6] With North Sea oil yet to be in production, the UK was reliant on imports for this resource. Once again, the UK found itself within a state of emergency as the 1973 Oil Crisis resulted in a fourfold increase in crude oil prices (Yergin, 1991). This crisis triggered global interest in the development of alternative energy sources and signalled the urgent need for the UK to develop a coherent energy policy.

As part of the revised government strategy, the Department of Energy (DoEn) was formed in 1974, which established the Energy Technology Support Unit (ETSU) (Kenward, 1974). The purpose of ETSU was to lead an alternative energy research and development programme, and establish feasible options for future renewable energy technologies.

The focus of research in the 1970s primarily explored wave energy, which had been indicated as highly suitable for the UK in early studies. A number of experimental devices were built, but by 1978 it had become clear that these were prohibitively expensive. In 1979, the incoming Conservative government signalled a reduction of the expenditure on energy research. While nuclear energy was again protected from cuts, '*non-nuclear research and development*' and '*energy conservation*' were seen as less important and the funding was reduced significantly. This led to the controversial termination of the UK tidal energy programme (Newton & Burch, 1985).

Following the reduction in funding, the priority of the ETSU research programme shifted towards onshore wind. Throughout the 1980s, ETSU continued to produce a range of studies and reports although there were limited attempts to develop working demonstration projects.[7] The only direct project to be constructed was a single 3MW turbine constructed in 1987 (DoEn, 1988b). However,

[6] "Primary Energy Consumption" includes all fuel used for heating, transport and electricity generation

[7] Some of their key studies include research into wind energy assessments (Newton & Burch, 1985) and energy from waste (Buck & Ader, 1985)

this would prove to be the conclusion of the UK government's direct involvement in wind energy, and was the last act of the UK renewable energy research programme.

Two key conclusions can be drawn from this period. Firstly, Wilson (2012) notes that renewable energy was still seen as a form of insurance policy. There was still a strong belief that nuclear power was the technology of the future. Secondly, the pursuit of large turbines that exceeded technological limits of the day reflected the government's belief that systems must be based around the same principles as conventional power systems, where bigger was seen to be better. International examples had proved 1MW turbines to be the most cost-effective at the time, yet plans were established to construct 4MW turbines, a size which would not be common until 20 years later (DECC, 2016a).

2.3.8 1990s: Privatisation of the Network

In 1988, the government set out the new direction for renewable energy with Energy Paper 55 *'Renewable Energy in the UK: The Way Forward'* (DoEn, 1988a). The plan proposed a market-led system to encourage commercial development in renewable energy with the aim of reducing government involvement.

The electricity supply industry within the UK was privatised in 1990, dividing the UK network into six regional bodies. The primary mechanism of support for renewable energy technologies in this time was the Non Fossil Fuel Obligation (NFFO), which was designed to support nuclear and renewable technologies. The NFFO operated by placing a levy on all consumers, and the newly privatised Regional Energy Companies were obliged to purchase electricity supplied from the NFFO suppliers.

The original NFFO schemes caused several issues. Firstly, the auction process rewarded power output, and therefore wind farms were sited in the windiest, often most remote and scenic locations. This results in power generation that is distant from the high voltage (HV) grid and key urban centres. Secondly, the tendering process was conducted in successive rounds, and created batches of parallel projects, giving rise to a perceived rush for wind power. It has been noted that these issues led to increased opposition of such projects and created barriers in the development of wind resources within the UK (Mitchell & Connor, 2004).

In addition, there was limited overlap between the NFFO and government research objectives. The three NFFO auction rounds prioritised the funding of landfill gas, small turbines and energy from waste while research had primarily focussed on larger wind turbines (Mitchell, 1996). By capacity, 80% of projects obtaining NFFO support were conventional landfill gas and Energy from Waste (EfW) projects (Elliott, 1996).

These issues reflect the reliance on the market to lead the development of renewable energy. The majority of renewable energy generation policies at this stage were market-based and led from a national perspective, which can arguably lead to short-term decision-making (Mitchell & Connor, 2004). Compared with interventions internationally, most notably Germany and Denmark, greater levels of participation are encouraged in energy planning from local communities (Centre for Climate Change Mitigation Research, 2015).

2.3.9 1998 to 2012: Regional Development Agencies (RDAs)

The Regional Development Agencies Act 1998 (HMCO, 1998) established 7 zones within the UK, with the aim of planning regional strategies for future development. As shown in Section 2.1, the period saw the increased awareness of the need to reduce emissions and the development of renewable energy. Part of the role of the RDA was "*to contribute to the achievement of sustainable development in the United Kingdom where it is relevant to its area to do so*".

A key aspect of the planning framework was the creation of Regional Spatial Strategies (RSS), which were designed to identify key investment opportunities within the region and drive economic growth. Planning Policy Statement 22 mandated that these RSS addressed renewable energy development for each region (UK Government, 2004).

During this period, the Utilities Act 2000 was established, which required electricity suppliers to provide a proportion of their sale from renewable sources. The Renewable Obligation (RO) was established and was designed to drive renewable energy development through a market-based mechanism. A Renewable Obligation Certificate (ROC) would be issued for each Mega Watt hour (MWh) of renewable energy generation. When the system was first released in 2002, each form of renewable energy technology received the same level of support of one ROC/MWh. This reflected the government's ambition to promote a market-led approach and not favour any particular technology. However, this system resulted in the deployment of more established technologies such as landfill gas and onshore wind over less developed technologies that were further from being commercial viable. It was not until 2009 that the differing levels of ROCs were offered to provide higher rates for the less commercially viable options.

Another major change in the traditional energy system was the introduction of feed-in tariffs (FITs). The policy mechanism was designed to accelerate investment in renewable energy technologies, and started in 2010. This policy has led to a large change in the way the national grid has operated, as will be discussed further in Section 2.7.

2.3.10 2012 to Present: Localism

Localism, or increased local governance, is a current policy within the UK influencing many areas of planning. Changes enacted through The Localism Act 2011 have given a general power of competence to all local authorities and gives them "*the power to do anything that individuals generally may do*" (DCLG, 2011). This has opened up many new opportunities for councils which were previously restricted in their involvement, and as a result, there has been increased interest in development of energy strategies.

In 2012, the RDAs were abolished. This move reflected an increasing trend for local representation in decision-making, and a shift away from top-down governmental structures. Local Enterprise Partnerships (LEPs) were formed to create voluntary partnerships between local authorities and businesses, with a total of 39 LEPS in England. The change in regional boundaries can be seen in Figure 2.7.

The aim of the LEPs is to help determine key priorities and lead economic growth and job creation within the local area. While the LEPs carry out some of the functions previously served by the RDAs, they are technically voluntary organisations that have not been designed to directly replace RDAs. As a result, there is a less clear and consistent administrative structure at a local level than experienced previously, and concerns have been raised that "*Power Vacuum*" has been created as there is an absense of local actors who are directly accountable for regional targets (CCLG, 2011). Recent UK government guidance demonstrate an expectation that local authorities will take a lead in the development of local electricity generation, through support to local communities, investment in local energy schemes, or more targeted approaches for specific subsets of public buildings, e.g. schools (DECC, 2015a). Furthermore, because of ongoing budget restrictions imposed on local government, local authorities are considering a range of revenue raising and efficiency saving options including sale of property and land, and the creation of alternative income streams (Adam et al., 2016). Such initiatives will be explored in Section 2.4.

2.3.11 Summary of Historical Development

The historical development of energy networks provides important context for the project, and highlights how energy planning scale has been shaped by a combination of technical and political drivers. It can be seen from the start of the 19th century that planning scale and political motives have shaped the direction of energy within the UK. Local stakeholders, notably local government

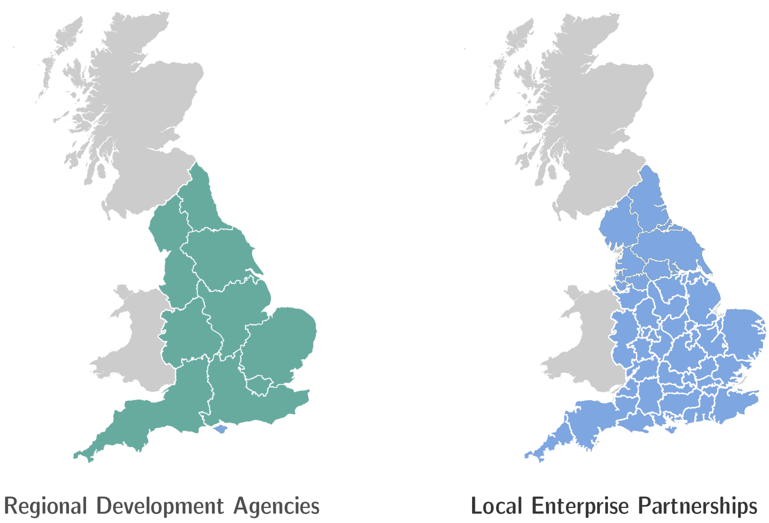


Figure 2.7: A comparison of boundaries for the Regional Development Agencies and Local Enterprise Partnerships, as defined in 2015.

organisations, were marginalised from energy governance during the post-war nationalisation of utilities. However, the recent administrative changes have provided an opportunity for local authorities to become involved again, as they have been granted greater powers through the Localism Act 2011. As noted above, the impacts caused by these recent changes will be explored further in the following sections.

It should also be noted that energy policy objectives relating to renewable energy have been driving at a national and regional level, notably through the NFFO and RO programmes. This highlights the issue that regional energy companies are seen as the key actors by the existing system, however there is evidence they may not necessarily be the most effective actors to deliver decentralised activities, with arguments being that greater local level planning would be more suitable (Bridge et al., 2013).

Finally, parallels can be drawn between the early development of the national grid and modern day renewable energy projects. The National Grid received much criticism for the perceived industrialisation of the countryside, with the purpose of providing electricity primarily for the use in urban areas (Sherry-brennan & Pearson, 2015). It is suggested that renewable energy technologies face similar challenges today, as renewable energy technologies have been indicated to require significant amounts of rural land to meet the energy needs which are largely concentrated within urban areas (Stoddart & Turley, 2012).

2.4 Recent Trends in Energy Governance

As explained in Section 2.3, local government has played a historically important role in the development of the UK national grid. The recent changes in government policy from 2012 onwards have increased local decision making, and have provided an opportunity for local authorities to be involved with energy planning. As shown in Figure 2.8, the majority of local authorities have ambitions for action on sustainable energy, with 82% active to some degree (Tingey et al., 2017). This section provides an overview of some of the key interventions which have been implemented by local authorities.

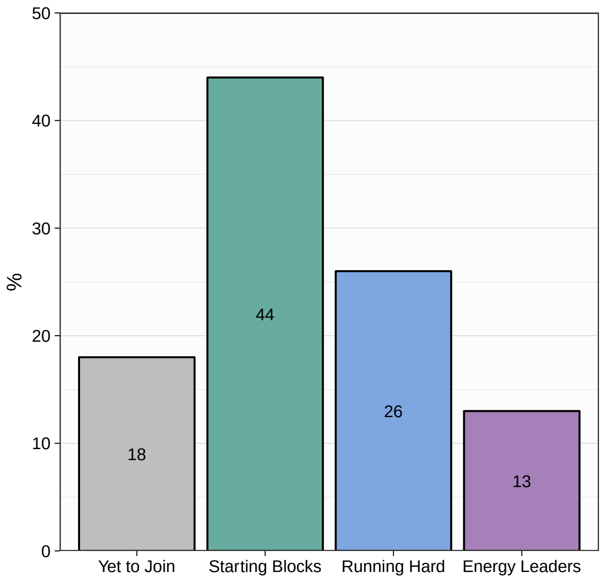


Figure 2.8: UK Local Authorities According to Level of Engagement in Energy Systems (Tingey et al., 2017).

2.4.1 Energy Interventions

Renewable Energy Producers

While Feed-in Tariffs have generally targeted individuals or business users, there has been increased interest from councils looking to deploy renewable energy technologies across its building stock within the city. A striking example is Portsmouth Council, which has deployed over 2MW of solar capacity across their properties within the city (Pratt, 2016). This investment has seen a return of between 8 and 12% and has helped provide an additional revenue streams for the council.

Energy Suppliers

There has been a growth in interest from local authorities to directly provide and sell electricity within their local authority by forming an Energy Service Company (ESCO). To this effect, Robin Hood Energy was established by Nottingham Council in 2016, and is the first council-owned energy firm to operate since the electricity network was nationalised in 1948 (Robin Hood Energy Limited, 2016). The company uses electricity generated from Energy from Waste plants, solar panels and waste food plants and also buys in gas and electricity from the market. Robin Hood Energy operates under a principle of always being cheaper than any of the '*big six*' providers so that users no longer need to continually switch providers. The effectiveness of the project has sparked interest across councils with many regions in the UK looking to follow this model, including Bristol (Bristol Energy, 2016) and Cheshire (Fairer Power, 2016).

Network Operators

There are a few examples of distribution networks being formed by local councils. These typically comprise heat networks that are used in conjunction with Combined Heat and Power (CHP) plant, which supply heating to buildings within a district. A few examples of CHP networks have existed since the 1980s in the UK, with Southampton providing one of the most well-known example along with Aston, Birmingham, which is now the largest operating CHP network in the UK (Engie, 2014). Local planning can be used to steer investments in renewable energy: as an example, Southampton City Council has preferential planning rights that encourage developments to connect to their established heating and cooling network.

City Energy Systems

There are international examples of cities taking the role of regulators, providers and promoters of solar, wind, hydro power, and biomass fuel as locally produced energy sources, including Freiburg, Germany (Kern & Alber, 2009), and off-grid solutions built in developing nations (Goldthau, 2014). The ultimate goal is to decouple municipal energy systems from centralised infrastructure and sources and to operate independent networks (Goldthau, 2014). This concept of running an independent system with no connections to a national grid is termed '*energy autarky*' (Mller et al., 2011). Such systems capitalise on the ability of local governance to create coordinated strategies and drive investment into low-carbon solutions (Riahi, 2015).

Recent trends in the UK have seen the development of the Core Cities initiative (CORE Cities, 2013). They argue that cities can and do more to solve energy challenges for the nation, however lack sufficient legislative powers to fully benefit from their proposals.

Energy Neutrality

Energy neutrality refers to "*the extent to which a district [...] can supply itself with sustainable energy generated within the boundaries of that district*" (Jablonska et al., 2011). Compared to the concept of energy autarky, neutrality does not negate being part of a larger network, and therefore energy can be transferred in and out of the region providing the annual contributions are balanced.

$$\sum_{j=1}^{n} E_{Demand} - E_{Supply} = 0 \tag{2.1}$$

There are several examples of regions within Europe which have successfully transitioned towards renewable energy, in particular Siena, Italy (Casprini, 2013) and Sams, Denmark (Waal & Stremke, 2014). While these areas have relatively low population densities, more densely populated regions within the UK and Europe have defined ambitious targets for an energy transition (CORE Cities, 2013). However, such regions are often unaware whether spatial characteristics of the region are suitable for their targets, and transition targets are more often set on aspirational targets than technological feasibility.

2.4.2 Summary

Changes granted through the Localism Act 2011 have provided an opportunity for local authorities to increase their involvement within the electricity generation sector. The examples shown have demonstrated a clear interest in the development of renewable energy from local authorities, and the different levels of development that have been pursued. However, it further highlights the importance of cities understanding the renewable energy technologies available to them in order for such approaches to be possible. Section 2.5 therefore provides an overview of key renewable and low-carbon technologies available.

It is important to note that the motivations for cities to develop energy systems stem from financial, not environmental, challenges. Within the UK, budgets for councils have been cut by 40% since 2010 and there are increasing pressures to generate income streams.

Cities appear to be in a strong position to drive the development of sustainable energy. However, Tingey (2017) notes that "*larger scale contributions from localised energy are likely to require clear direction from central governments*". Existing developments are largely optional for political authorities, and as such, there is much variation in the targets being set and the actions being taken.

2.5 Renewable & Low Carbon Technologies

It was shown in Section 2.1 that ambitious renewable energy targets have been set for the UK. This has resulted in a significant increase in renewable energy within the past decade, surpassing 30GW of installed capacity in 2016 (DBIES, 2016a). The overall annual electricity generation is shown in Figure 2.9, which highlights the exponential development of renewable energy technologies.

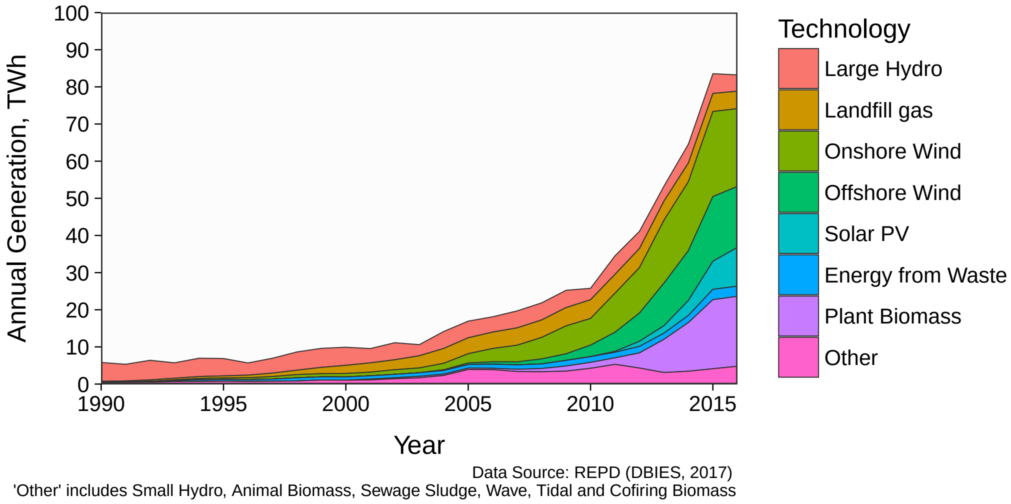


Figure 2.9: Annual electricity generation (TWh) from renewable energy technologies installed within the UK, 1990 to 2016.

This section provides an overview of the key technologies available and methods for renewable and low-carbon energy generation. In particular, this section is focussed on highlighting the suitability of technologies to be utilised by local authorities, either within their city limits or surrounding hinterland.

Installed capacities as of 2015 are in brackets by each title, and were taken from the Digest of United Kingdom Energy Statistics (DBIES, 2016a).

2.5.1 Types of Technology

Onshore Wind (Existing Capacity = 9188MW)

It has long been noted that the UK has a large available wind resource due to its position and high amounts of coastline, and it was previously predicted that UK has two thirds of the European Wind resource (Strachan et al., 2006). The onshore wind industry is one of the most mature renewable technologies in the UK based on installed capacity.

Whilst progress has been made in developing onshore wind, projects have experienced particular difficulty in gaining planning permission and projects often invoke strong opposition from local communities. Projects are often visually intrusive and may have negative ecological impacts if sited incorrectly.

Recent amendments to the planning of onshore wind schemes have changed planning approval process for wind energy projects. Firstly, local councils have become the primary decision-makers for planning applications for new onshore wind farms (HMCO, 2015). Until 2016, larger onshore wind energy projects of above 50MW were treated as Nationally Significant Infrastructure Projects (NSIPs), which meant that development consent of such projects was granted by the Secretary of State under the Planning Act 2008 (HMSO, 2008). However, legislative changes[8] have removed onshore wind projects over 50MW from the NSIP regime, returning decision-making authority to the Local Planning Authority (LPA) (Smith, 2016).

With the changes in planning for onshore wind, LPAs must take planning decisions in accordance with the policies set out in the National Planning Policy Framework. In addition, further considerations must be made so that "local people have the final say on wind farm applications." (HMCO, 2015). Potential areas will need to be allocated clearly in a local or neighbourhood plan, and maps showing the wind resource as favourable to wind will not be sufficient.

Offshore Wind (Existing Capacity = 5103MW)

There has been a rapid growth in the installed offshore capacity since 2010 as a number of large offshore projects have been developed. Being within coastal waters, these schemes have been controlled through the Crown Estate, and sites for potential developments have been released through a number of planning rounds.

Despite their location, offshore projects have still faced issues in achieving planning consent and encountered similar criticisms to onshore projects. For example, the 970MW proposed Nativus Bay Wind Farm was rejected in 2015, with the primary reason for this being the seascape, landscape and visual impact (DECC, 2015b).

Solar Photovoltaic (Existing Capacity = 9187 MW)

Solar PV systems are generally categorised into three types of system: residential rooftops, commercial rooftop, and ground mounted utility scale. Within the UK, the typical residential system is 4kW while the largest utility sized plant installed has been 69.8MW (as of November 2017).[9]

Driven by advances in technology and increases in manufacturing scale, the price of solar PV has experienced a fivefold decrease in price since 2010 (DECC, 2015b). Installed capacity surpassed onshore wind in 2016, making it the largest installed renewable in the UK. However, with a load factor of 10-12%, compared to a typical value of 30% for onshore wind, means that the annual generation of solar remains lower than onshore wind.

[8] Specifically, the Energy Act 2016 together with the Infrastructure Planning (Onshore Wind Generating Stations) Order 2016.

[9] Constructed in 2015, MOD Lyneham is the largest plant (DECC, 2016c)

Hydropower (Existing Capacity = 1477MW)

Large hydropower is the most established renewable energy technology and was largely developed in the 1950s and 1960s in the UK (DECC, 2016c). Future opportunities are limited due to the site specific limited sites available, and as such there are few opportunities to expand the technology.

Small Hydro (Existing Capacity = 282MW)

Small hydro is generally classed as projects smaller than 10MW (DECC, 2013). These sites will typically operate as run-of-river devices, with no large reservoir being formed. Similar to large-scale hydro, the requirements for small-scale hydro are largely site specific and therefore only present limited opportunities for development.

Wave and Tidal (Existing Capacity = 9MW)

Wave and tidal devices extract energy from the ocean. Despite early interest in marine energy from ETSU, the technology was largely abandoned due to the prohibitive cost of the technology. However, there have been recent developments of interest for tidal sources in the UK, with a number of example projects being developed in in Scotland, Cornwall and the Isle of Wight. In addition, there are considerations of tidal lagoons and barrages within the Severn Estuary. However, it is not expected for these technologies to be deployed at a larger scale until at least 2030 (DECC, 2013).

Landfill Gas (Existing Capacity = 1061MW)

The use of landfill methane gas for power generation began in 1985, and was quickly increased in the 1990s as a consequence of the NFFO (Brown & Maunder, 1994). The gas is generated from the decomposition of organic material in the waste stream.

Future opportunities for the expansion of natural landfill gas are limited, as the European Waste Directive (European Commission, 2008) has mandated a reduction in the amount of organic waste disposed of at landfill. Consequentially, the amount of landfill gas production is expected to decrease, and therefore this resource will reduce with time.

Biomass (Existing Capacity = 2619MW)

Biomass covers a diverse range of fuel sources and technologies. In summary, it utilises the combustion of various organic materials to produce electricity or heat. Most biomass in the UK is currently used for large-scale power production in traditional power stations such as Drax, which is located away from city centres. This resource, however, is largely imported from overseas, and there are concerns surrounding the long-term sustainability of such resources. However, there is growing interest in the use of biomass for combined heat and power (CHP) which can be used within urban regions.

Energy from Waste (Existing Capacity = 925MW)

Energy from Waste (EfW) involves the combustion of municipal and industrial waste to produce electricity and heat. It has become a more popular option in recent years as landfill capacity has reduced and limits have been imposed on the amount of waste generated, and it can be seen that there has been a large increase in installed capacity since 2010.

While EfW is considered a low-carbon technology, there are concerns about the use of waste as a source of fuel. In particular, the technology relies on combustible material for operation, and recyclable materials such as cardboard and plastic both have high calorific values. There has been evidence to suggest that EfW technologies can therefore discourage the pursuit of increased recycling rates with local authorities (DECC, 2013).

2.5.2 Renewable Energy Planning Scale

Within the context of the thesis, the various technologies have different scales at which planning is typically led, as highlighted within Figure 2.10. Many technologies are out of the scope of local decision-makers, including offshore wind and tidal projects, which are coordinated by national planning decisions. On the other hand, technologies including Solar PV and onshore wind are predominantly planned at a local level. These issues are central to the research theme, and are expanded upon within the summary of the chapter.

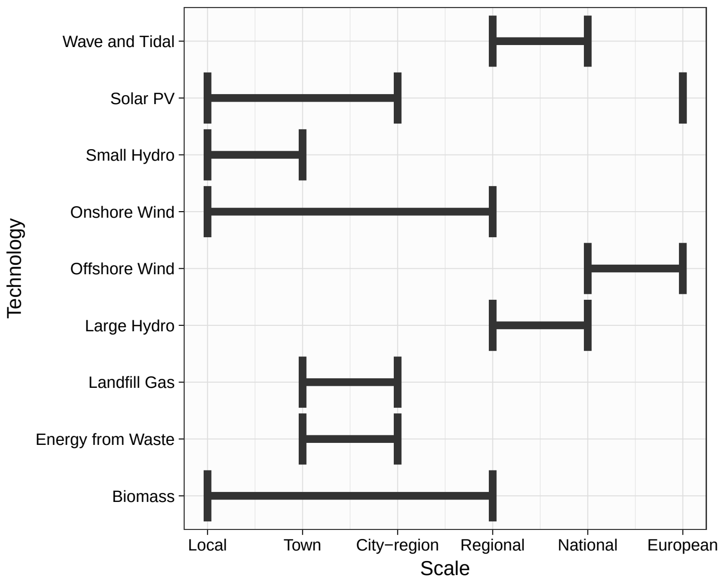


Figure 2.10: A comparison of energy technologies and the spatial scale at which planning is influenced.

2.6 Spatial Renewable Energy Capacity Assessments

As part of the historical development of energy systems presented in Section 2.3, there has been repeated interested from national and regional government to assess the potential of renewable energy technologies. This section provides a brief overview of these studies and explains some of the key limitations of the approaches used.

2.6.1 1970s: ETSU Research

Throughout the 1970s, a number of renewable energy potential studies were conducted within the UK (ETSU & AEAT, 2001). Such studies largely focussed on the physical scale of the resource, and did not quantify what could feasibly be utilised. However, by the 1980s there was increased assessment of the economic potential of technologies, with onshore wind and tidal energy placed as the most promising technologies (Buckley-Golder et al., 1984).

2.6.2 2001: Regional Capacity Assessments

Interest in regional energy assessments increased in the early 2000s, as renewable energy development strategies were included within the spatial strategies for UK RDAs. These reports were the first large scale assessments of renewable energy of the UK, and utilised Geographical Information Systems (GIS) to assess the potential for renewable energy. However, there was no fixed definition of how the assessment should be conducted, and more importantly no guidance about the level of renewable energy which each region must aim to produce. As a result, there were large variations in targets that were set for the regions, resulting in large variations between the outputs of these studies. As an example, it was seen that only four of the thirteen regions studied set any renewable energy target, and these targets varied between 5 and 15% (OXERA, 2002).

2.6.3 2010: Regional Capacity Assessments

To address the concerns raised within previous studies, the Department of Energy and Climate Change (DECC) commissioned a methodology to consistently assess potential renewable energy capacity across the UK (SQW Energy & Land Use Consultants, 2010). The methodology outlined the following stages, which aimed to determine renewable energy targets for cities and regions:

1. **Naturally Available Resource**: quantify the naturally available renewable energy resource.
2. **Technically accessible resource**: estimate how much of the natural resource can be harnessed using commercialised technology.
3. **Physical constraints of high priority**: explore the physical barriers to deployment such as areas where renewables schemes cannot practically be built.

4. **Planning and regulatory constraints**: apply a set of constraints relevant to each renewable technology that reflects the current planning and regulatory framework, such as excluding from the assessment areas and resources that cannot be developed.
5. **Economically viable potential**: consider the cost of technology, energy commodity prices and cost of capital.
6. **Deployment constraints**: identify supply chain constraints e.g. maturity and capacity of the supply chain to deliver the required renewable fuel or technology and to deploy the technology.
7. **Regional ambition target setting**: set the level of renewables to be targeted within the region based on political and legislative drivers.

Stages 1 to 4 of the methodology was applied to each region to reassess the renewable energy targets for each region, with no specific guidance provided for Stages 5 to 7. Despite the establishment of a consistent methodology, there were still difficulties in producing comparable analysis across all the regions. Limited data availability in several regions meant that alternative methodologies were occasionally adopted to derive results (AECOM, 2011).

Additional concerns were raised about the underlying assumptions within the analysis. A review of the regional studies reflected views that the analysis significantly overestimated both onshore wind and micro-generation capacity, and felt the analysis was too simplistic to fully model the challenges in implementing these technologies (Stoddart & Turley, 2012). In particular, it was noted that the methodology was oversimplified in its approach to the challenges of planning.

As a final observation, the studies assumed that there is an equal split of the decarbonisation targets of 80% regardless of the potential for renewable energy exploitation in the region. Clearly, in the urban areas such as London, the scope for renewables is reduced, whilst rural regions can meet the required levels relatively easily (Oudes & Stremke, 2018). Such spatial dependencies of renewable energy targets are discussed further within the Literature Review.

2.6.4 2014 onwards: Local Enterprise Partnerships

The abolition of RDAs has led to a restructuring of the renewable energy planning goals, as regional target setting is no longer used to drive forward planning. While the administrative boundaries have been removed, the challenges of implementing national targets at a local level still remain, and local authorities are starting to investigate their potential role in the development of renewable energy. To this effect, there been interest in assessing renewable energy potential within Local Enterprise Partnership (LEP) regions. Two studies have been identified that utilise similar approaches to the 2010 DECC methodology, but are partially adapted to reflect the local challenges, being conducted for the Solent (Arup, 2014) and Liverpool LEPs (LEP Co., 2017).

A limitation of the new LEP-led approach is that as voluntary organisations, there is no legislative requirement for energy strategies to be formulated. As a result, there has been inconsistent coverage of such studies, and such studies lack any overall coordination which was present previously. In addition, LEP regions can overlap, and therefore the same resource is possible to count within two separate estimates.

2.6.5 Summary

While the DECC low-carbon assessment methodology provides a useful framework to assess renewable technologies, there are limitations in the suitability of the result. A major barrier in these studies has been in understanding the impact of regulatory and planning influences. This issue of model validation will be explored further within the literature review to form a greater understanding of the physical and regulatory constraints.

In addition, the studies have been conducted at a predetermined planning scale, and that a strong methodological nationalism is exhibited (Cowell et al., 2017). As such, there spatial aspects are often not fully considered, such as proximity in actor networks or any kind of sub-national variations (Spath & Rohracher, 2012).

2.7 Energy Transition Challenges

It was outlined within the historical development that the traditional energy system is modelled around large-scale power plant operating within an interconnected network (Hughes, 1983). Such an approach has enabled economies of scale and lower reserve capacity to be achieved. However, the recent developments in renewable energy capacity are beginning to challenge these operating principles. This section therefore explains the key challenges relating to the development of renewable energy, with focus on spatially dependent issues.

2.7.1 Changes in Grid Composition

Current legislation, energy policy and economic constraints have made it increasingly difficult for large-scale traditional power stations to operate. The European Large Combustion Plant Directive (European Parliament, 2001) has set strict emission standards on large thermal plant which has resulted in many closures, with many coal and oil-fired power stations no longer being able to operate economically.[10] The closure of these very large power systems is contrasted with the deployment of small-scale generation throughout the UK. The downward shift in the size of generation and the tendency to decentralise is leading to the establishment of more distributed generation.

2.7.2 Separation of Supply and Demand

Renewable energy policy has largely been driven at a national level, and, as a result, projects have been constructed where the resource is best nationally. For example, it is noted by Wilson (2012) that windy sites *"do not generally coincide with the area of maximum industrial or domestic demand for electricity. Indeed they tend to lie in the more remote areas of natural beauty."*. This is demonstrated by Figure 2.11, which highlights that spatial patterns are clearly visible, with wind energy projects largely built in Scotland and Wales, solar installations largely located in the South West.

The geographical mismatch between supply and demand requires transmission networks to help transfer electricity between these regions. Such transmission has resulted in capacity constraints in electricity transmission network, with projects in the South West being delayed by up to 6 years as additional capacity is developed (Western Power Distribution, 2015). Such upgrades are not only expensive, but have delayed the progress of renewable energy development within parts of the UK.

Temporal aspects are also a key consideration of renewable energy, as renewable technologies are largely intermittent. There is a requirement to develop storage technologies to help balance supply and demand of technologies. However, this project focusses on spatial imbalance, not temporal imbalance.

[10] Some notable examples include Longannet, Didcot and Fawley Power Stations (Scottish Power, 2015).

2.7.3 Planning Barriers

It was noted within the review of the government planning studies that existing renewable energy methodologies were viewed to overestimate the capacities of renewables, and a large problem was the inability to account for challenges in planning (Stoddart & Turley, 2012). These concerns can be further supported by the low acceptance rates of wind energy projects within the UK, although technologies face differing levels of acceptance, as shown in Figure 2.12. The most contested project type is onshore wind, with over 50% of projects being rejected planning permission (DECC, 2016c). Such rejection rates suggest that models are failing to accurately account for all the issues surrounding the development of onshore wind energy, and therefore do not provide a suitable tool for identifying suitable wind energy sites.

2.7.4 Spatial Scale of Planning

A persistent theme in the analysis of environmental governance is that there is a mismatch between the scale of a problem and the institutional arrangements (Cowell et al., 2017). Analysis conducted at too small or big scale can be accused of being 'too localized' and 'too centralized' respectively. Whilst there are concerns that existing planning is being conducted at too large of scale, it is also suggested that cities are too local of a resolution for action to be effectively driven. There is evidence that cities alone are too small scale to be able to deliver change.

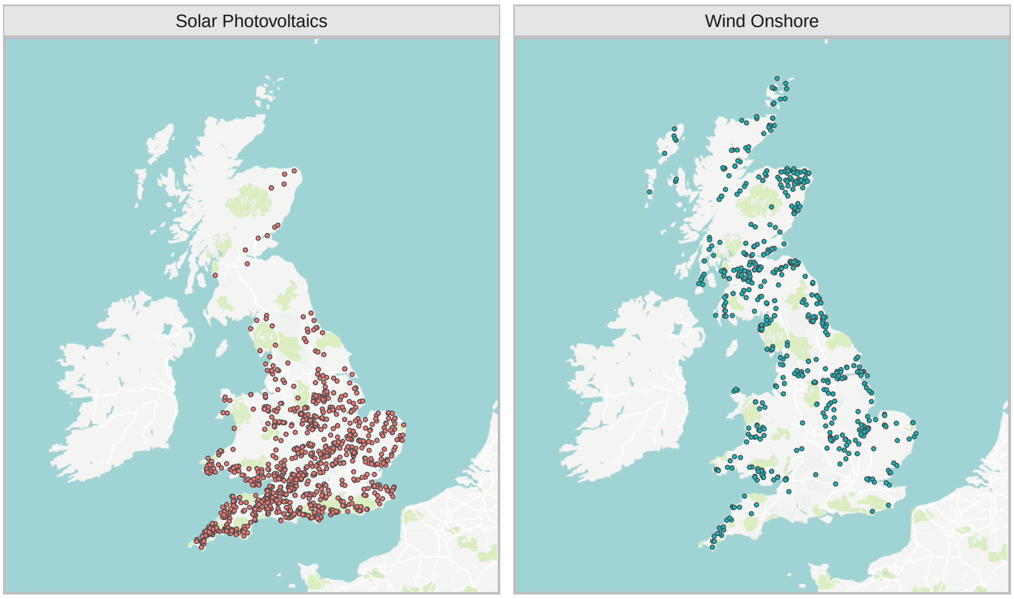


Figure 2.11: The location of installed PV and onshore wind sites within the UK as of May 2016. Only sites greater than 1MW are displayed. Data source: Renewable Energy Planning Database (DECC, 2016c).

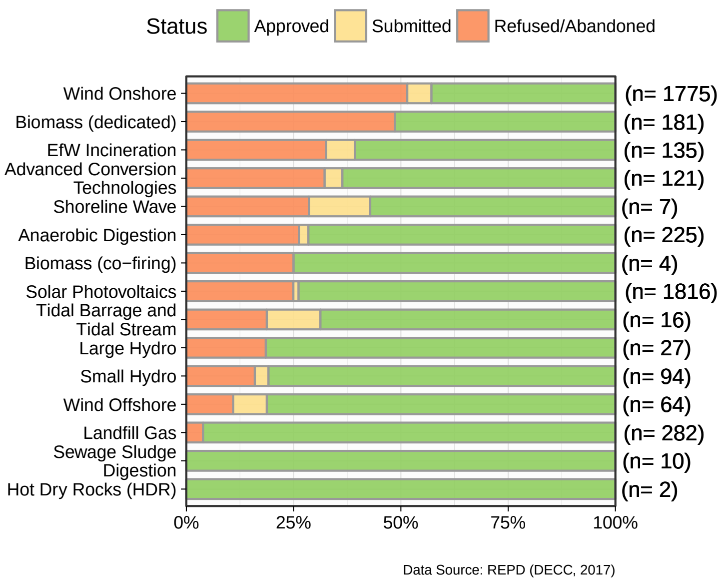


Figure 2.12: Project type and the proportion of projects that receive planning permission.

2.8 Conclusion

The chapter has aimed to outline the background motivation for the thesis, and position the work within the broader political and social context. This has focussed on the UK's commitment to reduce GHG emissions, and the required development of renewable and low-carbon technologies to meet these targets.

The issue of spatial scale has become increasingly important within recent developments in the UK energy sector. Whilst the traditional development of energy systems has been led at a national and regional level, there has been increasing shift in decision-making required for renewable energy technologies to a local level. There has been little questioning of these geographical imaginations which underpin political authority (Bridge et al., 2013), and as such there is a limited understanding as to whether the existing arrangement is most suitable for the transition to renewable energy technologies.

The historical context of the UK energy system was outlined in Section 2.3. It was shown that the territorialisation within the UK energy system have constantly evolved throughout its history, and that such changes within these spatial imaginations for planning have been shaped by both political and technical challenges. With changes in governmental powers in 2011 through the Localism Act, there has been a surge in interest from local authorities to be involved within the local energy sectors. It is argued within literature that such bodies are the ideal scale at which the low-carbon transition should best be led. However, such involvement is largely motivated by economic benefits for the councils, and there are no legislative requirements for councils to meet sub-national carbon targets.

Section 2.5 demonstrated that the UK has a range of renewable energy resources available for development. However, the suitability of technologies is highly influenced by the scale at which planning is considered: projects including large hydropower schemes and offshore wind energy are typically planned nationally, whilst onshore wind and solar projects have a much greater local perspective. It is therefore crucial that the scale of energy planning is integrated within the resource assessment of technologies when identifying potential locations for development.

There has been a high level of interest within government to assess the renewable energy potential for a region. Whilst the DECC methodology was developed in 2010, it was commented that these approaches grossly overestimated the level of renewable energy which could be installed within a region (Stoddart & Turley, 2012). Receiving planning permission is a major limitation within such studies, and over 50% of onshore wind energy projects have been rejected planning permission, highlighting a potential gap between existing modelling approaches in determining suitable sites.

2.8.1 Refinement of Study Scope

Within the context of scale, here has been a growing emphasis on cities as a driver for low carbon energy development, with calls for greater autonomy to be provided to cities. It is argued that such control would empower cities and enable them to drive the radical change required to transition to a low-carbon future, and that a decentralised planning approach is more suitable for renewable energy resources. However, there are concerns that cities have a limited resource availability for renewable sources, and there is a lack of understanding within current policy of the optimal scale at which energy should be planned.

While it was highlighted in Section 2.5 that there are a range of renewable energy technologies for development, it was decided that only a single technology should be selected for development in the scope for this study. Such a narrowing of scope was preferred as it would allow for a more detailed assessment to be made, rather than the more general "*all-technology*" approaches which are commonly used within governmental studies presented within this chapter.

Based on the recent growth of interest from city-regions to lead sustainable development and low-carbon energy, it was decided to explore opportunities that may be developable by a local authority or region. For the following reasons, it was decided that that onshore wind energy should be selected for the study:

- Onshore wind is an established technology, with the lowest Levelised Cost of Energy (LCOE) when compared with competing technologies (UNEP, 2016).
- Changes in planning for onshore wind have transferred greater responsibility to the local authorities granting greater powers to local bodies to influence development (Smith, 2016).
- As will be discussed further within the Literature Review, a number of research gaps had been identified within existing methodologies to examine the regional potential for onshore wind energy.
- Onshore wind energy provide a large database of existing projects. As presented in Chapter 6, there have been over 2000 wind energy projects proposed within the United Kingdom.

Regarding other technologies, the following reasons were suggested to exclude the technologies within this project:

- **Solar**: there are issues surrounding local grid capacity caused by the load matching of the technology. Both daily and seasonal spikes fit poorly to existing load profiles, and therefore there are limitations to the wide scale development of such technologies.
- **Offshore Wind**: although projected to play a major role within the UK energy system, the development of such projects is not under the control of councils or regions.
- **Biomass**: this technology requires dedicated land for use of growing crops, which creates major land use issues and competition with existing agricultural practises.
- **Small Hydro**: this technology is highly site specific, which limits the development opportunities across the country.
- **Large Hydro**: the scale of investment required for such projects is beyond the scope of a local authority, and are typically led at a national level. Further to this, there are limited opportunties for further expansion of the resource.

These conclusions do not intend to suggest that these other technologies are not suitable for future research. The purpose of defining a scope of select technologies was to help define a narrower and more focussed approach for this thesis. As will be discussed further in the future works, there are opportunities to integrate other renewable energy technologies into the methodologies proposed within this thesis.

Chapter Summary

- Ambitious emission reduction targets have been set for the UK, yet there is evidence insufficient progress is being made.
- Energy systems are intrinsically spatial issues, yet there has been limited assessment of the geographical underpinnings of such systems.
- Changes to renewable energy is challenging the spatial planning scale of energy planning, with a shift to decentralised planning.
- Historically, local authorities played a key part in the development of electricity networks. However, the influence was reduced over two centuries of policy and planning changes.
- Local authorities are emerging as a key actor within energy planning and are leading a number of initiatives to develop local energy sources.
- There has been consistent interest from governments to assess the renewable energy potentials, with the last methodology developed in 2010.
- The UK has a wide range of suitable renewable energy resources available for development including wind, solar and biomass.
- Onshore wind energy was selected as the technology to be studied as a case study for development, due to its low cost, potential for further development and the availability of data for modelling.

Chapter 3

Technical Background of Onshore Wind Assessment

Chapter 2 highlighted the development of renewable energy and positioned the work within the broader social and political context. It was shown that national scale renewable energy planning in the UK is creating many challenges in renewable energy development, and demonstrated limited understanding of the appropriate planning scale for renewable energy development. Much of the current planning process does not reflect the emergence of cities or regions as the new scale of economic power, or does not consider whether planning at this scale is even suitable for leading renewable energy development.

In addition, it was shown that there has been interest in mapping renewable energy potential for regions, with several methodologies developed to assist regions in establishing targets (SQW Energy & Land Use Consultants, 2010). However, it is argued that these existing governmental renewable energy analyses appears to overestimate potential capacity, particularly due to the difficulties in modelling the impacts of planning constraints on developments.

Chapter 3 provides the technical background of the research area to help frame the academic literature presented within the following chapter. The aim is broken into the following objectives:

- to explain the development of geospatial modelling systems and their use within spatial planning.
- to detail the parameters typically used in assessing wind energy site suitability.
- to detail the various assessment techniques which can be used in identifying suitable sites for wind development.
- to reflect upon the presented techniques and define the scope for the literature review.

3.1 Geospatial Modelling and Planning

Geographical Information Systems (GIS) are defined as "*tools which are designed to capture, store, manipulate, analyse, manage and present spatial or geographical data*" (Malczewski, 2004, p. 4). Development in GIS systems has grown from its infancy in the 1960s to forming an integral part of spatial planning, and the technology has wide applications within transport, energy and various land-use problems.[1]

The spatial distribution of renewable energy supply (RES), the inherent dependence on site-specific constraints and the overall cost dependence on spatial attributes makes GIS a key tool in energy management (Petit, 1995). A key advancement in GIS modelling was the introduction of cartographic modelling and map algebra techniques into computer-assisted mapping (Malczewski, 2004). Central to this approach was the use of overlay analysis, whereby a new layer (output layer) is produced as a function of two or more input layers.

One of the most useful applications of GIS modelling for planning and management is to map and analyse suitable land-use. Land-use suitability analysis aims to identify the most appropriate spatial pattern for future land use, based on specific requirements, preferences or predictors of some activity (Hopkins, 1977). These will be explained in more detail within Section 3.3.

There has been a changing perspective of GIS within planning decisions since the early development in the 1960s, which saw the planning paradigm focus on applied data science (Malczewski, 2004). This approach uses the underlying assumption of a direct relationship between the data processing capability and information availability, and the quality of planning on the other: the better the data processing capabilities, the better the quality of planning.

The 1980s saw an increasing disappointment in the applied data science model of planning, as it was argued that scientific approaches failed to address the relationship between planning and the society being planned (Malczewski, 2004). This disillusionment led to the adoption of a strong political perspective on planning, whereby it was recognised that planning involves socio-political systems composed of interest groups with conflicting values and preferences (Friend, 1997). By viewing planning in this way, the key underlying concepts became public participation, negotiation, compromise, redistribution, consensus building and conflict management and resolution (Malczewski, 2004).

The change in understanding of and approach to planning also altered the use of GIS models, and empirical studies revealed that planning is more than the collection and provision of information that can improve the policy-making process (Harris, 1989). GIS planning moved from being a closed black box, to becoming a more communicative and participatory tool in the planning process.

While some elements of the planning process are well defined, there are significant components of subjective knowledge, common wisdom and myths within the process. The concept of combining these *objective* and *subjective* elements in a computer-based system lies at the heart of a Spatial

[1]For a detailed account of the historical development in GIS, see Malczewski (Malczewski, 2004)

Decision Support System (SDSS). These systems is designed specifically to tackle the issue of semi-structured problems, and combines judgement and computer-based programs to aid the decision-making process (Malczewski, 2004).

Spatial decision-making forms two key two elements: an action *(what to do?)* and location *(where to do it?)*. A Spatial Decision Support System (SDSS) is based on the fundamental analytical functions of GIS; attribute or spatial queries, proximity, buffer analysis, neighbourhood analysis, network analysis and spatial modelling. Various combinations of these are used to analyse the geographical data to help identify the most suitable sites for development (Malczewski, 2004).

There are three stages to the decision-making process applied within the context of a SDSS (Simon, 1979):

1. **Intelligence**: this phase consists of finding, identifying, and formulating the problem or situation that calls for a decision. This has been called *deciding what to decide*, and selects the evaluation criteria by which the options will be assessed.
2. **Design**: this phase normally involves GIS analysis to develop a solution set of spatial decision alternatives. The integration of decision analytical techniques is critical for supporting this phase (Ascough II, J. C.; Rector, H. D.; Hoag, 2002).
3. **Choice**: finally, a particular set of alternatives is selected from those available. The end product of this phase is a decision that is suggested to be carried out.

Further detail of these concepts is provided in Section 3.4.

3.2 Wind Energy Geospatial Siting Parameters

A wide range of environmental, technical and social parameters influence the acceptability of a site for onshore wind energy development. This section focuses on the key parameters which are most regularly used within studies, and primarily focusses on those which have been included within the government renewable energy assessments described in Section 2.6. A more detailed review of parameters is also included within the Literature Review to identify those less frequently used.

3.2.1 Wind Resource

The availability of a sufficient wind resource is a key parameter for a wind turbine to be economically viable. *Wind Speeds* are affected by the ground roughness and obstructions including buildings and trees, all of which can adversely impact wind speed. The higher above ground a turbine is positioned, the higher the average wind speed it will receive. As wind speeds are rarely measured at the height of the proposed turbine, the wind profile power law can be used to calculate the wind speed at for the turbine against a reference point, and is denoted as:

$$v = v_r \left(\frac{z}{z_r} \right)^{\alpha} \tag{3.1}$$

where v is the wind speed at height z, and v_r is the known wind speed at a reference height z_r. The exponent α is an empirically derived coefficient that varies dependent on the stability of the atmosphere, and is typically 1/7 used within wind resource assessments. An example wind speed profile plot is shown in Figure 3.1a, as calculated for an estimated wind speed plot of $4ms^{-1}$ at 10 metres above ground.

The *Turbine power* is a function of the wind speed, and can be calculated as:

$$P = \frac{1}{2} \rho A v^3 C_P \tag{3.2}$$

where P is the power output in Watts, ρ is the density of air, A is the swept area of the wind turbine, v is the velocity of the wind, and C_P is the power coefficient.[2] As can be seen by the equation, there is a cubic relationship between wind speed and power, and consequentially even a small change in wind speed has a significant impact on the potential power generation.

Whilst wind power increases cubically, turbines will have a maximum rated power and will be designed to operate at this power across a range of wind speeds. Beyond a certain speed, a turbine will be designed to shut off to prevent damage. As a result, there is a relatively narrow band of wind speeds where they operate at full capacity, with the typical output from a turbine shown in Figure 3.1b.

When siting a wind turbine, it is more important to understand the electricity generation potential for a turbine across a period of time, most typically expressed annually. As wind speed data is

[2] This value varies for each turbine, but reaches a maximum value of 16/27 (59.3%) and is known as *Betz Limit*.

usually recorded as a sample of the wind speed or an average speed over some time period, it must be converted to a time-series wind speed. The Wiebull distribution is most frequently used to transform wind speed data to calculate annualised electricity generation estimates (Seguro & Lambert, 2000). The statistical tool provides an estimate of how often winds of different speeds will be seen at a location with a certain average wind speed, and can be expressed as:

$$f(x) = \frac{\alpha}{\beta}\left(\frac{v}{\alpha}\right)^{\alpha-1} e\left(-\left(\frac{v}{\beta}\right)^{\alpha}\right) \tag{3.3}$$

where α and β are the shape and scale factors, and v is the average wind speed. For onshore wind assessments, these factors are typically specified as 2. Figure 3.1c provides an example plot for a $5ms^{-1}$ wind speed, which has historically been used as the lowest acceptable wind speed for a wind turbine to be economically viable within the UK (SQW Energy, 2010).

Finally, the electricity generation (GWh) over a period of time can be expressed as:

$$E = T\int_{v_{out}}^{v_{in}} f(v)p(v) \tag{3.4}$$

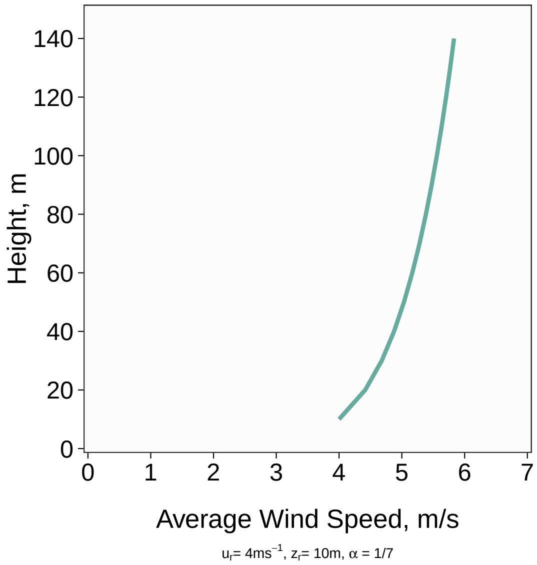
where $f(v)$ is the probabilistic density function of the wind speed v, $p(v)$ is the power curve of the turbine and T is the production time period. Electricity generation starts at the turbine's cut-in wind speed v_{in} and stops at cut-out wind speed v_{out}.

3.2.2 Turbine Size

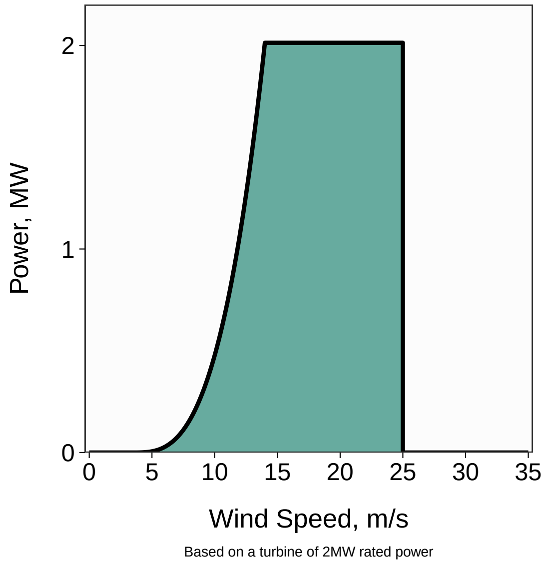
As shown in Equation 3.2, the swept area A of the turbine influences the electricity generation potential. Turbine studies will typically assume a standard wind turbine size dependent on the technology available at the time of the study. There has been the general progression in turbine size, and technologically feasible turbines can reach 10MW, although such turbines are typically only used in offshore projects. Where it has been stated, studies have typically utilised turbines between 1 or 2MW (SQW Energy, 2010; Watson & Hudson, 2015; Yue & Wang, 2006). To verify the choice of this value, the general increase in turbine size with time was plotted in Figure 3.1d, which shows the largest onshore turbine constructed in the UK per calendar year along with the annual average. While the maximum size turbine reached 3.5MW in 2015, the average size has remained around 2MW since 2006. Such a 2MW turbine will typically have a blade size of 50 to 60 metres, with a tower height of between 80 and 100 metres (Vestas, 2017).

3.2.3 Turbine Development Density

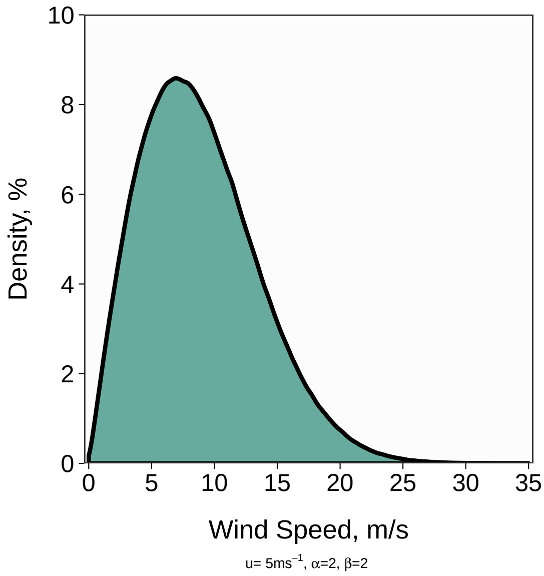
Turbines require a minimum spacing distance to prevent interference with each other, which can reduce operational efficiency (Newman, 1977). Theoretical models have typically operated on a minimum spacing of seven times the rotor diameter for turbines within a hypothetical "*infinite*" wind-farm (Meyers & Meneveau, 2012), which equates to around 750 metres for a typical 2MW turbine. In reality, models have assumed that turbines will be installed in smaller pockets with less



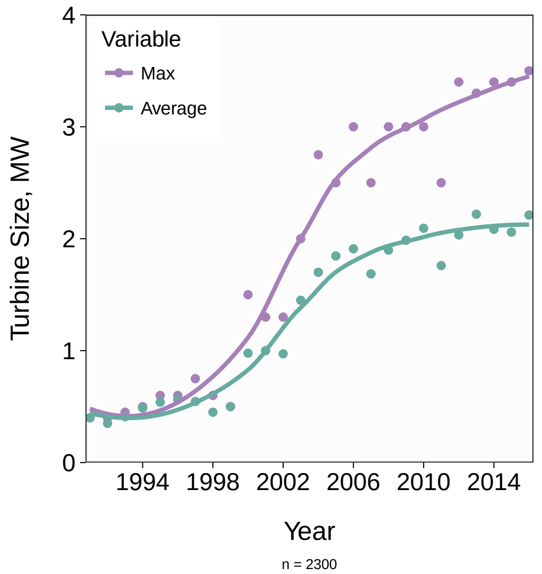
(a) Wind Power Height Profile



(b) Typical Turbine Wind Speed Power Profile Curve



(c) Weibull Wind Speed Distribution



(d) The max and average turbine size for onshore wind energy projects within the UK

Figure 3.1: Example wind power load curves used to estimate power output of a wind turbine.

risk of interaction, and therefore spacing of 500m or a density of 4 turbines per kilometre squared has been more commonly used (SQW Energy, 2010).

3.2.4 Social Geographic Features

A range of social geographic features are typically used with studies to identify suitable sites for onshore wind. These are explained as follows:

- **Urban Areas**: A particularly important aspect is the interaction with urban areas, as the potential issues arising from noise and visual intrusion make them generally unpopular. Sites typically aim to be located away from urban areas, with many studies being based on a minimum of 500 metres separation (Baban & Parry, 2001; Miller & Li, 2014; Watson & Hudson, 2015).
- **Transmission Network**: Proximity to the electricity transmission network is also seen as an important parameter (Baban & Parry, 2001). Being close to a transmission network can reduce the need to construct additional power lines, which causes both considerable added expense and increased complexity in planning.
- **Site Access**: Site access is required for both the construction and ongoing maintenance of the turbine, and therefore studies often assess the proximity to the road network. This is considered an important parameter in locating suitable sites. A minimum buffer distance must also be applied to roads to provide a topple distance of their tip-height plus 50 meters (DFT, 2013).
- **Slope and Gradient** The gradient and elevation of the site is used as an important parameter for site selection (Baban & Parry, 2001; Chaudhry, 2008). Slightly sloped and elevated sites typically have improved wind speeds as they experience less impact from ground cover, while overly steep sites can become inaccessible for construction.
- **Airports**: Wind turbines have the potential to impact the operation of airports, both from the physical obstacle formed and the interference with radar stations (Civil Aviation Authority, 2016). As a result, airport safeguarding rules within the UK state that any wind energy project within 30km of an airport must demonstrate no potential for interference with the airport (DFT, 2002).

3.2.5 Visual Impacts

The visual impact of onshore wind turbines make them particularly sensitive to landscape designations within the UK (Baban & Parry, 2001; Watson & Hudson, 2015). Many recognised landscapes are protected within the UK, including 15 National Parks and 46 Areas of Outstanding Natural Beauty (AONBs) (Natural England, 2016a). An extensive list is provided within Section 7 of the report, as the designations are dependent on the study region.

3.2.6 Ecological Impacts

Wind turbines can have impacts on living organisms such as birds and sensitive natural environments as follows:

- **Bird and Bat Sensitivity**: Wind turbines can have a negative impact on wildlife, providing a collision risk to birds and bats, and a disturbance of habitats (Drewitt & Langston, 2006). As a result, planning guidance requires that the potential impact of turbines against birds is assessed. Bird sensitivity is often required for the detailed planning of potential sites, but regional assessments often utilise a growing number of bird sensitivity maps which highlight potentially unsuitable regions for development (Pearce-Higgins & Green, 2014).
- **International Statutory Sites**: Where wind farms are proposed, their development should not cause adverse effects on the integrity of statutory international sites. Within the UK, there are a range of international statutory conservation designations which can impact the location of wind energy projects.
- **National Statutory Sites**: Along with the internationally specified protected areas, there are a range of national designations specified by the UK government which are designed to protect sensitive areas.

Specific details of the International and National Statutory sites are provided within the Data Collection in Chapter 7.

3.3 GIS Assessment Methods

Section 3.2 highlighted the range of parameters extensively used within GIS modelling of onshore wind energy. This section summarises the main types of GIS methods used within SDSSs for onshore wind assessment, before highlighting their suitability for this project.

Table 3.1 provides an overview of the methods covered within this section. A few specific examples are provided of studies which utilise each method within this section. However, these are more fully expanded within a detailed review of studies in Section 4.2.

Table 3.1: A summary of onshore wind GIS assessment techniques.

Method	Assessment Result	Applicability
Multi-criteria Decision Analysis	Suitability	Site Identification
Boolean	Accept / Reject	Target Setting
Viewshed Analysis	Visibility Impact of Turbine	Visibility Impact

3.3.1 Boolean Overlay

The Boolean overlay method assesses site suitability using a set list of criteria and applying non-compensatory combination rules to these values (Malczewski, 2006a). Suitable sites are identified if they meet the condition criteria specified.[3] Therefore, if there are N criteria, and a minimum value of X is required, then the site suitability is calculated as:

$$\text{Site Suitability} = \begin{cases} 1, & \text{if} \quad (Max_i > X_i > Min_i) \quad \text{for} \quad i = 1, 2, 3 \ldots N \\ 0, & \text{otherwise} \end{cases}$$

This method was applied for the government-led renewable energy studies described in Section 2.6.3 (SQW Energy, 2010). It has also been used in a range of academic studies which are discussed further within the literature review. However, while such studies are useful for establishing the maximum potential for a region, they provide limited guidance on which sites are best to be utilised and therefore have limited applicability to development when applied in isolation.

This Boolean rule method can be combined with other methods to specify regions of exclusion, before more advanced analysis is conducted on the remaining areas (Van Haaren & Fthenakis, 2011). This will be discussed in detail within Section 4.2.

[3] These may be minimum wind speeds, maximum site gradient, or a specified buffer distance around sensitive features such as airports.

3.3.2 Multiple-Criteria Decision Analysis

Multiple-Criteria Decision Analysis (MCDA) methods deal with the process of making decisions in the presence of multiple objectives (i.e. minimise cost, carbon emissions and social impact) (Malczewski, 2006b). Options are assessed by comparing the relative score of sites based on a number of suitability criteria, which can consider economic, technical and political variables as shown in Figure 3.2. Using these various data layers an overall score is calculated for the site based on the separate criteria.

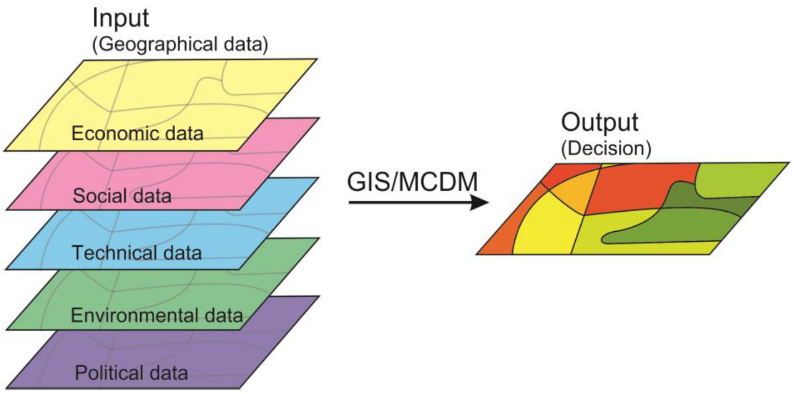


Figure 3.2: Geospatial MCDA approach (Rikalovic et al., 2016).

It has been noted that MCDA helps reflect a more realistic model of the challenges in wind development and assesses the suitability of locations within a given region (Pohekar & Ramachandran, 2004). More than 30 studies have been identified which use MCDA within the locating of wind energy projects, as discussed further within the literature review in Chapter 4.

3.3.3 Viewshed Analysis

Predicting whether one point is visible from another (intervisibility analysis) and predicting the total area that is visible from a single point (viewshed analysis) are standard features within GIS software (Wheatley, 1995). Viewshed analysis has been used in a variety of applications but has been particularly useful in assessing the visual impact of wind energy developments (Kidner et al., 1997; Minelli et al., 2014; Moller, 2006; Rafal Wrozynski et al., 2016).

Whilst viewshed analysis is used for modelling onshore wind, it is most typically used on potential sites which have gone through an initial screening process and as part of the detailed planning stage; the analysis requires the exact positioning of turbines to produce accurate results. The results from the analysis produce the Zone of Theoretical Visibility (ZTV) mapping the area where a wind farm will theoretically be totally or partially seen. While the method is useful on a site-by-site assessment, existing literature has focussed largely on one single viewpoint, or at most for a very small number of observers (Tabik et al., 2012). This limitation is due to the computational requirements of such analysis, and also the fact that single-point algorithms cannot efficiently be scaled to all points. To the author's best knowledge, there are currently no effective methods for this to be used across a region.

3.3.4 Suitability of Approaches for Project

This section has presented the three key GIS techniques which have been used with the assessment of onshore wind site suitability. Each have a range of benefits regarding the results produced, however they vary in their suitability for regional assessments and potential site identification. As this study requires the formation of a model to assess the land suitability across a region, and to identify the most suitable sites for development, MCDA provides the most suitable form of GIS assessment, and is expanded further within the following Section.

3.4 GIS Multiple-Criteria Decision Analysis

While an overview of MCDA was provided in Section 3.3, this section expands upon the different MCDA techniques typically utilised within onshore wind assessments.

3.4.1 MCDA Classifications

Models can be defined according to three parameters as follows:

1. **Decision Rules**: Multi-objective decision analysis (MODA) versus multi-attribute decision analysis (MADA);
2. **Decision Makers**: Individual versus group decision making;
3. **Uncertainties**: Decisions under certainty (deterministic) versus decisions under uncertainty (probabilistic and fuzzy).

For the *Decision rules*, Objectives are the reflection of the desire of decision makers and reflect the direction on which the decision should be decided (Pedrycz, 2016). Multi objective decision-making (MODM) is known as the continuous type of MCDA and therefore involve the design of alternatives that optimise or at least satisfy the objectives set.

Attributes are the characteristics, qualities, or performance characteristics of alternatives (Pedrycz, 2016). Multi attribute decision-making (MADM) is related to making preference decisions (that is, comparison, choice, prioritisation, and/or ordering) over the available alternatives that are characterised by multiple, usually conflicting, attributes.

For renewable energy assessments, there is typically a single objective (is the site suitable for selection) and a range of attributes (resource availability, proximity to features etc.). As a result, models have typically used MADM techniques for the selection of sites (Malczewski, 2004; Mardani et al., 2015). The literature therefore focuses on these techniques for further discussion.

For *decision makers*, if there is a single goal-preference structure, then the problem can be referred to as a single decision-maker's problem. This is regardless of the number of individuals actually involved, and studies are completed from an individual point of view. Alternatively, if the individuals (interest groups) are characterised by different goal-preference structures, then the problems become that of group decision-making (Malczewski, 2004).

Finally, if the decision maker has perfect knowledge of the decision environment, then the decision is made under conditions of certainty. Such analysis is termed *deterministic*. In many real-world situations, there are aspects which are unknown or very difficult to predict, and such analysis is considered as decisions under situations of uncertainty. This uncertainty can further be divided into two kinds of uncertainty: limited information about the decision situation, or alternatively fuzziness (imprecision) concerning the description of the semantic meanings of the event, phenomena or statements themselves. These create *probabilistic* (stochastic) and *fuzzy* decision-making problems depending on respective type of uncertainty involved.

Hansen (Hansen, 2005) provides the example of wind turbine noise as an example of the usefulness of fuzziness within the data. It may potentially be clear that a noise of 60 dB or more is unquestionably annoying and less than 20 dB is not a problem, however there may be no clear point at which this transition happens. A fuzzy relationship could therefore define the degree of membership (known as the "possibility") of a location in the set called "at risk", with values greater than 60dB have a value of 1.0 while those lower than 20dB have a membership value of 0.0. Between these two extremes, values would be scaled according to one of many range of possible membership functions. This process of transforming a binary scale to create a redefined scale is termed "*fuzzification*" (Hansen, 2005).

Many analysts choose to model spatial decisions as occurring under a condition of certainty because of insufficient information (Malczewski, 2004). Consequentially, the majority of GIS-MCDA articles fall into the deterministic category although in reality they contain aspects of probabilistic and fuzzy decision-making (Daim et al., 2013; Mardani et al., 2015).

3.4.2 Methods of MCDA

As mentioned in Section 3.3.2, there are a range of MCDA methods which can be applied to renewable energy modelling. This section the key types of MCDA which have been applied within literature.[4]

3.4.2.1 Weighted Sum Method (WSM)

The WSM is the most commonly used method of MCDA, especially in single dimension problems (i.e. economic, environmental or social criteria). If there are M alternatives and N decision criteria then the best alternative is the one that satisfies the following expression:

$$A_i^{WSM} = \sum_{j=1}^{n} w_j a_{ij} \quad \text{for} \quad i = 1, 2, 3, ...N \tag{3.5}$$

where A_i^{WSM} is the WSM score of the best alternative, N is the number of decision criteria, a_{ij} is the actual value of the i^{th} alternative in terms of the j^{th} criterion, and w_j is the weight of importance. The primary reason for the popularity of the weighted summation and related methods is that the approaches are very easy to implement with the GIS environment using map algebra operations and cartographic modelling (Malczewski, 2004).

[4]A range of other methods have been proposed, although they were not considered suitable for the assessment of onshore wind. For a comprehensive review of the main MCDA methods, the author recommends Pohekar (2004). These include 1) *Ideal/reference point analysis types* 2) *Linear-integer programming* (TOPSIS, MOLA) and 3) *Heuristic search/ evolutionary/ genetic algorithms*.

3.4.2.2 Analytic Hierarchy Process

Analytic Hierarchy Process (AHP) is a method proposed by Saaty (Saaty, 1980), and provides a mathematically based tool to deal with complex, unstructured and multi-attribute problems. A relational hierarchy is formed for the criteria, and pairwise comparisons of these are made to calculate the relative importance of the two parameters being compared. The results from the pairings can then be used to derive parameter weightings that can be used in a similar fashion to the WSM outlined previously.

One of the benefits of AHP is that it allows the relative importance for varying parties to be calculated, and can help gain an understanding of the viewpoints of key actors within the decision-making process (i.e. developers, planners etc.). However, a drawback is that it can be very time consuming to implement, and the pairing process is inherently subjective.

3.4.2.3 Outranking Methods

The preference ranking organisation method for enrichment evaluation (PROMETHEE) and the elimination and choice translating reality (ELECTRE) are both similar methods used to compare potential options. They perform a pair-wise comparison of alternatives to rank them with respect to a number of criteria. However, they do not directly specify whether a project should be developed, but instead highlight which are the best options of the provided alternatives.

Such methods are relatively limited in application for regional assessments, although extensively used within different forms of land use assessment where only a small number (less than 100) of specified sites have been provided (Malczewski, 2006b).

3.5 Conclusion

This chapter aimed to provide the necessary technical context for the research. In Section 3.1, it was highlighted how GIS modelling approaches have been extensively used within the modelling of renewable energy technologies. Such tools are highly suitable as they provide a method to combine the many different information layers that are often required for locating suitable sites for development. However, spatial problems often comprise a range of objective and subjective elements, and as a result, there has been increased development in the use of SDSS to counter these challenges.

Section 3.2 outlined the key environmental and technical parameters which are commonly used within the decision-making process for onshore wind energy projects. These largely focus on the technical constraints, including the available wind resource, distance to the electricity transmission network etc. The broader social issues surrounding the acceptability of sites is expanded upon within the Literature Review in the following chapter.

Three geospatial modelling techniques to assess onshore wind energy sites were presented in Section 3.3, including Boolean, MCDA, Viewshed analysis or combinations of these. As the emphasis of this study is to identify regional wind energy capacities, the Boolean and MCDA methods were selected as the key assessment techniques to be explored further.

Having defined the scope of the approaches to MCDA, Chapter 3.4 expanded upon the techniques of MCDA. Three methods were presented which can be used to determine the weighting of parameters within the decision making process, primarily WSM and AHP. These are explained further within the Literature Review.

Chapter Summary

- GIS developed as a tool to assist spatial planners, and is extensively used within modelling of renewable energy technologies.
- Spatial decision support systems are used extensively to aid in spatial decisions within semi-structured problems.
- A range of parameters are typically used within the assessment of onshore wind energy, including wind speed, proximity to urban areas and protected landscapes.
- Whilst a number of techniques are available within GIS modelling, Boolean and MCDA methods are primarily used for regional assessment of onshore wind technologies.
- The Weighted Sum Method (WSM) and Analytic Hierarchy Process (AHP) are commonly used methods for determining the parameter weighting within MCDA.

Chapter 4

Literature Review

Chapters 2 and 3 framed the background information of the research issue, highlighting the relevant technical framework for the analysis. This chapter builds upon these previous chapters and provides a review of the academic approaches used to address the issues of renewable energy planning and scale, with a focus on onshore wind energy. The objectives of the chapter are as follows:

- to synthesise the rationale for the research questions based on the research background presented.
- to explain the approach used to conduct the literature review, highlighting the scope of literature included.
- to highlight existing research conducted within wind energy site modelling.
- to identify limitations within onshore wind geospatial modelling techniques.

4.1 Methodology

Research Questions

Two key research areas were raised within Chapter 2. Primarily, there is uncertainty within energy planning of the spatial scale at which energy should be planned and developed. Whilst cities appear to be emerging as a dominant power within the UK, there is a limited understanding as to whether they are in the best position to lead the development of renewable energy technologies.

In addition, there was evidence that existing geospatial modelling approaches grossly overestimate the potential for renewable energy technologies. There is a clear issue within wind energy modelling, as over 50% of such projects have been rejected in planning. Based on these concerns, the following research questions were therefore developed to be explored within the literature review:

1. What methods are used internationally to assess the site suitability of wind energy projects?
2. What factors influence the planning acceptance of wind energy projects?
3. How can model results be checked and validated against existing development patterns?
4. How is spatial planning scale be considered within existing GIS modelling?

These will be expanded upon within each section of the literature review.

Review Approach

Based on the defined questions, the following areas were researched using the listed search terms:

- **Onshore wind energy site location methods**: "*wind resource assessment*", "*wind energy siting*", "*wind energy GIS*", "*onshore wind GIS*"
- **Planning Acceptance of Wind Energy**: "*wind turbine planning acceptance*", "*wind energy planning acceptance*"
- **Spatial Scale modelling**: "*energy spatial scale*"

The literature review focussed primarily on academic journal publications, identified through *Google Scholar* and *Science Direct*. For onshore wind energy location modelling there has been large amount of non-academic interest in the area, with a number of government studies conducted as highlighted in Section 2.6. These studies have not been included within the literature review.

The review has focussed on the most recent published papers in onshore wind as these are more clearly related to current planning practice. Papers were therefore primarily focussed on since 2014 (the start of the PhD), recording all sources found within this period that were relevant to the research problem. Papers before this date were also selected, but only those which were instrumental in the development of knowledge.

4.2 Onshore Wind Site Location

In total, 23 GIS-MCDA wind energy studies were identified within the scope of the literature review. An overall summary of these studies is Table 4.1, with each summarised using the following categories:

- **Location**: in which Country/Continent was the study conducted
- **Scale**: the administrative unit covered (Continent, Country, Region/State, County)
- **Area**: the area (km^2) of the study region. Where no value was explicitly stated, an estimate was calculated.
- **Resolution**: the cell size of the spatial modelling
- **MCDA Method**: the decision-making method used, as described in Section 3.4.2.
- **Weighting Method**: the method used to determine the relative importance of parameters within the model.
- **References**: which other GIS-MCDA were directly cited by the study.

Many models at first appeared suitable, however many only dealt with a single aspect of the wind energy siting issue, primarily economic wind potential. Some recent examples include De Meij et al. (2016) and Mas'ud et al. (2017). Due to the number of these studies, they were not considered within the scope of the study, with the focus primarily on understanding how models combined economic, technical and social parameters within a decision-making framework.

Offshore wind energy GIS studies were initially considered within the scope of the review, due to similarities between the two technologies and the similarities in aspects of the siting problems. However, it was deemed that this broad scope provided no additional merit to the literature review, as there are large differences to the way that social issues are modelled within such studies. In particular, onshore wind turbines can generally receive greater local opposition due to the perceived negative visual impacts, and the more localised issues which projects can generate, such as noise and site access requirements (Toke et al., 2008). Offshore wind studies were therefore excluded from this review.

This section of the literature review is broken into three parts: firstly, the development of papers is shown chronologically to highlight the sequential development of the studies, drawing attention to the main themes of development within the literature. Secondly, a critical review of the literature is conducted to explain the gaps identified within the literature. Conclusions are finally drawn from these two sections within the final stage of the work.

4.2.1 Chronological Development of GIS modelling

Voivontas et al. (1998) provides one of the earliest examples of renewable energy site assessment with a case study applied to Crete. A SDSS was developed to evaluate renewable energy potential and the financial analysis of investments. A range of digital maps including wind speed, road

Table 4.1: A summary of GIS-MCDA studies reviewed.

ID	Year	Author	Country	Scale	Area	Res	MCDA Methods	Weighting Source	References
23	2017	Kazak et al.	Poland,	Region	4500	-	WSM	Unspecified	-
22	2017	Manomaiphiboon et al.	Thailand	Country	513e3	1000	Boolean	Econometric	-
21	2017	Baseer et al.	Saudi Arabia		2.2e6	-	Boolean, WSM	AHP	1 3 5 6 7 8 12 14
20	2017	Liu et al.	China	Country	10e6	1000	Boolean	Econometric	-
19	2017	Mentis et al.	Africa	Continent	30e6	5000	Boolean	Econometric	10 13 15 18
18	2016	Siyal et al.	Sweden	Country	447e3	1000	Boolean	Econometric	10
17	2016	Sanchez-Lozano et al.	Spain	Region	4456	-	Boolean, WSM	AHP	6,8
16	2016	Herran et al.	Global		-	10000	Boolean, WSM	Unspecified	-
15	2015	Noorollahi et al.	Iran	Region	29530	200	Boolean, WSM	Unspecified	2 6 6 8
14	2015	Atici et al.	Turkey	Region	2400	2000	Boolean, ELECTRE	AHP	2 5 7 8
13	2015	Watson and Hudson	UK	Region	17094	90	Boolean, WSM	Literature	2 3 4 5
12	2014	Miller and Li	US	Region	20000*	200	Boolean, WSM	Unspecified	4 5 8
11	2014	Wang et al.	Japan	Region	13782	100	Boolean	Literature	2 7
10	2013	Gass et al.	Austria	Country	84000	100	Boolean	Literature	1 5
9	2013	Neufville	Jamaica	Country	11000	1000	Boolean, WSM	AHP	2
8	2011	Van Haaren	US	State	141300	1000	Boolean, WSM	Econometric	2 3 5
7	2011	Szkiliarz and Vogt	Poland,	Country	312679	500	Boolean	Econometric	-
6	2010	Janke	US	State	270000	1500	WSM	Unspecified	1 2 4 5
5	2010	Aydin et al.	Turkey	Region	30000	-	Boolean	OWA	1 2
4	2006	Yue and Wang	Taiwan	Region	125	-	Boolean	-	-
3	2005	Hansen	Denmark	Region	600*	250	Boolean	Unspecified	-
2	2001	Baban and Parry	UK	County	1600	1000	WSM	Unspecified	-
1	1998	Voivontas et al.	Crete	National	8303	2000	Boolean	-	-

networks, airports were used to assess suitable locations for wind energy installations, with Boolean restrictions specifying zones of potential development. The LCOE was then calculated at a 4km^2 resolution for the suitable sites selected to determine the most economic sites to be developed.

Baban and Parry (2001) provided a key stage in the development of onshore wind assessments. They conducted the first major analysis within the UK to identify suitable wind energy sites using GIS-MCDA models, assessing the wind potential for a 40 x 40km region in Lancashire. Criteria for the model were identified through surveys with various organisations in the UK (60 councils and 4 wind energy companies), and considered a range of environmental, economic and planning constraints. A pairwise comparison method was used to assign the relative weighting to the parameters, and suitability determined using the WSM. The results of the analysis were composed of classes from 0 to 10, where 0 represents ideal locations and 10 represents unsuitable locations.

Hansen (2005) conducted an assessment in Jutland, Denmark, utilising fuzzy variables within their analysis combined with Boolean exclusion criteria. The result produced site suitability maps scoring from 0 to 1 at a cell size of 250 metres. While the author commented that that "*weighting the various layers is perhaps the most critical part in the analysis*", a "*common sense*" approach was used to select the variables, with no justification provided within the analysis.

Yue and Wang (2006) assessed wind energy within a region of Taiwan using a similar approach as adopted by Voinvontas et al (1998). However, the method only used a Boolean approach to determine whether sites were suitable, and therefore there was limited use as a model to identify suitable sites against marginal options.

Aydin et al. (2010) assessed the environmental impact of wind turbines within Western Turkey. The methodology applied fuzzy logic principles to determine suitable sites based on two parameters: "*sufficient potential for wind energy generation*" and "*satisfaction of most of the environmental objectives*". MCDA utilised Ordered Weight Averaging (OWA), a method similar to WSM but used specifically for fuzzy logic models (Yager, 1988).

Janke (2010) conducted GIS analysis of wind and solar farms in Colorado. The analysis used a combination of Boolean rules to define absolute limits, combined with WSM methods being used to calculate a site suitability score for the other regions. The research was largely based on the methodology specified by Baban and Perry (Baban & Parry, 2001). The author provided no justification for the selection of the weighting parameters for this model, raising questions surrounding the validity of the model.

Van Haaren (2011) assessed the wind capacity in New York State using a SDSS. Boolean exclusion parameters were used to identify non-suitable sites, and an economic driven model was used to determine the economic viability of projects across the region. An interesting comparison was made between the results from the model against existing wind developments in the state, and the study noted that there was a good match between the model and actual developments. However, it is unclear whether the model was only compared once completed, or whether the location of existing projects was used to "*tune*" the model within the development.

Szkliniarz and Vogt (2011) conducted an economic assessment of potential wind turbine sites in a region of Poland. Boolean rules were used to specify exclusion zones, but again the study noted "*there are no specific mandatory recommendations relative to the site assessment for wind farms*". Compared to other models reviewed in this section, this study had a greater economic emphasis and aimed to produce greater understanding of expected load curves and power production costs of turbines within the region.

Gass et al. (2013) provided an economic assessment of onshore wind in Austria. Exclusion criteria were used to identify potentially developable sites, and then LCOE calculations were used to assess the economic viability of the sites. In effect, land suitability was based on the economic parameters (wind speed, proximity to grid) and built upon the analysis methodology outlined by Voivontas et al. (Voivontas et al., 1998).

Neufville (2013) further developed the use of AHP in their study of site suitability in Trinidad. Five experts were used to formulate the AHP model, and were from the sectors of 1) *academia*; 2) *land management*; 3) *urban and regional planning*; 4) *sustainable energy* and 5) *wind farm* *development*. Interestingly, the results of the AHP resulted in a strong weighting towards resource availability and less consideration of the social impact of projects, with wind speed and proximity to settlements having weightings of 37% and 2% respectively. This highlights a potential limitation of the AHP '*expert panel*', as it does not appear that these members had a socio-political background, instead largely focusing on the technical challenges of development.

Miller and Li (2014) developed a model to assess development in Northeast Nebraska, USA. The research follows a broadly similar approach to that of Janke (Janke, 2010), with a two-layer Boolean/WSM method used to set exclude areas and score the remaining areas. Similar to several previous studies, no justification or explanation was provided for the selection of the weighting parameters.

Watson and Hudson (2015) assessed central Southern England for wind and solar energy suitability using an AHP method. Being the first known literature study to assess wind in the UK since Baban (2001), the methodology built upon much of the work conducted in the previous study. It is interesting to note that wind speed had a 55% weighting within the site suitability score, highlighting that technical challenges were prioritised over visual, ecological and economic constraints.

Atici et al. (2015) proposes a MCDA model applies a novel ELECTRE methodology to rank potential sites. The first stage is pre-elimination of non-viable sites using Boolean criteria, and the second stage is evaluation of available sites using ELECTRE. This study is unique in the reviewed literature in its use of a ranking method of potential sites; however, the model studied a comparatively small area when compared to similar studies.

Noorollahi et al. (2015) conducted a two-stage wind assessment of Iran using Boolean and WSM methods. While the model integrated many variables within the exclusion zone stage of the analysis, the only three used to calculate the WSM were the economic parameters 1) *proximity to power lines*; 2) *distance to access roads* and 3) *wind speed*. As with many other models, there was no justification for the use of the weightings within the WSM.

Since 2015, there has been continued global interest in the research problem of locating wind farms. These studies have largely built upon the approaches built within existing studies but applying the models new study regions (Baseer et al., 2017; Mentis et al., 2017). In addition, there has been the continued development of econometric models, with the main parameter for site consideration of such models being the overall cost of electricity (Liu et al., 2017; Manomaiphiboon et al., 2017; Mentis et al., 2017; Siyal et al., 2016).

4.2.2 Review of GIS-MCDA Literature

The review highlighted 23 GIS-MCDA studies developed for the assessment of onshore wind site suitability. The wide range of countries across the globe in which studies have been conducted demonstrates a clear international interest in the research problem, with Figure 4.1 graphically highlighting this coverage.

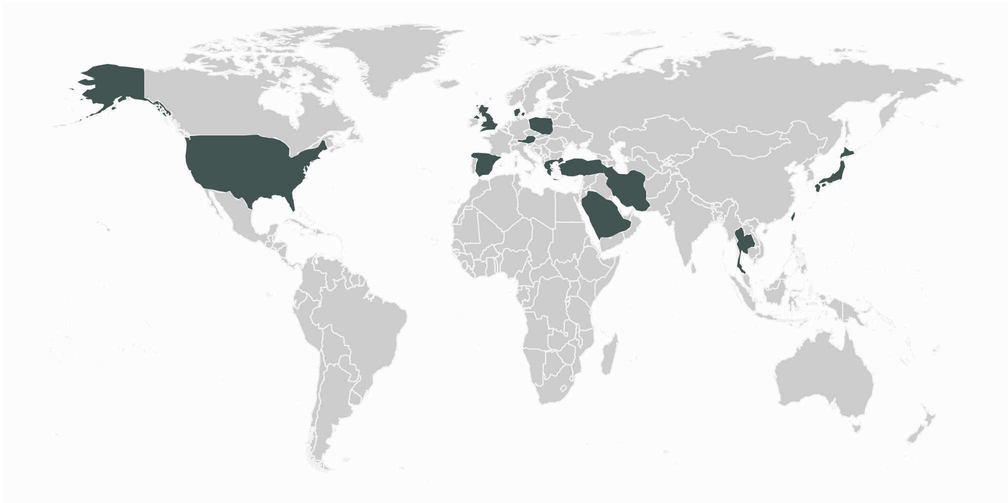


Figure 4.1: Location of onshore wind energy GIS-MCDA studies referenced within the literature review.

It is important to acknowledge the country in which the study was conducted. It was observed that there were differing approaches based around the country in which the study was conducted, with varying priority for the environmental, social and technical criteria. In particular, European studies generally placed a greater emphasis on the social aspects of wind farms when compared to other studies reviewed. It is argued that these differences result from the differing institutional and regulatory controls that influence wind energy developments within different studies. Similar parameters were used throughout the studies, and predominantly considered the geospatial siting criteria outlined in Section 3.2. It was noted that studies in Europe and the US typically considered more parameters, potentially reflecting the wider availability of open data that is available within developed nations.

None of the studies reviewed attempted to model demographic or social influences beyond the use of proximity areas. It is suggested that this omission fails to fully factor in the impact that social challenges present on the suitability of sites for development. There is evidence to suggest that socio-demographic issues can influence the chance of wind energy projects achieving planning approval. In particular, it has been noted within literature that developers were *"keen to avoid relatively privileged communities and target areas where people are thought to less likely put up a fight"* (Horst & Toke, 2010). This issue is discussed further within Section 4.3.

A common aspect between all studies was that a Boolean approach was used to exclude undevelopable areas, whereby a list of criteria is set which exclude the site from development if any single criteria is not met. However, the studies have large differences between both the parameters used and the exclusion distance surrounding each type of land, as demonstrated in Table 4.2 which highlights some of key studies. It is suggested that such differences stem from two reasons:

1. **Wind energy development is regionally specific**. For example, a less populated region may be able to be more selective in where they install wind turbines, and therefore may exclude areas closer to urban areas. Studies in the US have placed greater buffers around

urban areas (1500 metres) (Janke, 2010) than those conducted within the UK (500 metres) (Baban & Parry, 2001; Watson & Hudson, 2015).

2. **There are very few "hard" rules internationally stating where wind turbines can and cannot be built**: as such, models largely rely on the guidance of local specialists to determine suitable locations. Such experts will have varying experience and knowledge of their local region.

Table 4.2: Exclusion distances used within key onshore wind energy GIS-MCDA studies reviewed, highlighting the limits used within Boolean rules.

	Economic			Planning			Ecological	
Study Area	Wind speed	Power grid	Roads	Forests	Airports	Urban	Lakes	Study
UK	-	-	-	-	-	500	500	(Watson and Hudson, 2015)
UK	5 m/s	10000	10000	500	-	2000	400	(Baban and Parry, 2001)
Turkey	200 W/m^2	-	-	4500	4500	1500	3750	(Atici et al., 2015)
Denmark	200 W/m^2	-	-	550	6250	1000	450	(Hansen, 2005)
USA	-	Cost	5000	-	-	2000	3000	(Van Haaren, 2011)
Poland	-	200	100	500	3000	500	200	(Sliz-Szkliniarz and Vogt, 2011)
Sweden	-	200	200	-	2500	500	100	(Siyal et al., 2015)

* Note: The Units are in meters (m) unless otherwise specified.

For the selection of the best sites within the non-excluded areas, there are predominantly two approaches which have been applied: 1) *Weighted Sum Method* and 2) *Economic selection*. Whilst the WSM studies combined economic, social, and environmental parameters in an attempt to find the most suitable sites across multiple factors, the economic models solely based the suitability of potential sites on the Net Present Value (NPV) of potential investments. It was observed that economic models typically were applied in regions where there appeared to be less social contention against projects while European studies typically utilised a WSM method.

As discussed within the technical literature in Section 3.4, the selection of weighting scores for model parameters is an important consideration within MCDA (Malczewski, 2004). Despite this, a number of studies provided no justification for the weighting used (Kazak et al., 2017; Miller & Li, 2014; Noorollahi et al., 2015; Silva Herran et al., 2016). This raises concerns about the validity/transferability of these studies, as site suitability of models could be highly influenced by the selection of different parameters.

Many of the MCDA studies placed a very high ranking on the resource availability of the site (Neufville, 2013; Watson & Hudson, 2015). Such models reflect the priorities of the project developer, who must seek to maximise the economic returns on a project. However, in countries such as the UK, the land-use planning consent regime is not concerned with the energy yield of proposed wind developments (Sturge et al., 2014). Instead, local planning decisions will typically be made on the assessment of local impact of projects, most notably the visual impacts of projects and the opposition of local communities (Smith, 2016).

The locations of operational wind turbines were integrated into several studies (Aydin et al., 2010; Gass et al., 2013; Miller & Li, 2014; Van Haaren & Fthenakis, 2011; Watson & Hudson, 2015). However, these were largely used only as a form of discussion, and the information was not directly used to develop 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 (2015) noted "*operational wind farms in South Central England were predominantly located in areas suggested to be of lower suitability*", suggesting that the model inaccurately assessed site suitability in the region.

Table 4.1 highlighted the interconnection within the existing literature, as denoted by the *Reference* column. It can be noted that the early studies established much of the framework which has been within wind energy studies (Baban & Parry, 2001; Voivontas et al., 1998). Whilst there have been developments on these methodologies since, the overall approach of recent analysis has largely been unaltered. Many recent studies are still largely based on the approaches outlined within these initial studies (Baseer et al., 2017; Watson & Hudson, 2015)

It can be observed within the literature that there is a trend for models to assess increasingly large areas. It is argued that this reflects the increase in computational power available to a researcher, and the wider availability of datasets, and a prevailing assumption that "*bigger is better*". However, this potentially overlooks the highly localised issues which can limit the development, and applying a "*one-size-fits-all*" approach may not be the most suitable for regions which may have large diversity.

4.2.3 Critique of GIS-MCDA Literature

The combined Boolean/WSM method is commonly applied within literature for the assessment of onshore wind turbines, and it is argued that this is a suitable method to assess the suitability of wind energy sites within the UK. However, there is limited consideration of the assumptions underlying the model. In particular, there is often a lack of understanding of the weights assigned to the attributes and the consequent impact on the results. It is noted within the literature that MCDA is highly sensitive to the weights used within the assessment, and failing to accurately specify these can create inaccurate models (Malczewski, 2004).

Although AHP has been used within some studies to determine the weighting of parameters, this approach is still highly subjective and ultimately reflects the views of those who have been selected to be part of the analysis. From the studies cited, experts and academics were primarily chosen, with no involvement of local citizens who may be impacted by projects.

A potential gap between modelling approaches and actual development patterns can be highlighted by the low acceptance rates of wind energy projects within the UK, shown previously within the background information. It is proposed that this gap between modelling and reality could be influenced by two factors:

1. **Incorrect parameter weightings are being assigned**. As seen with previous studies, a high weighting is often applied to wind resource (Watson & Hudson, 2015). Prioritising the resource may be leading to the selection of sites which are less socially acceptable.

2. **Influential parameters are not being included within the analysis**. Existing studies place low emphasis on socio-demographic issues, and instead prioritise the technical and economic parameters. Although the methodologies attempt to model social issues by avoiding sites near urban areas, literature suggests that there may be more complicated interactions beyond those of simply spatial proximity (Horst & Toke, 2010). These issues are explored further in Section 4.3.

GIS Approach

Overall, the approaches adopted by the GIS models reviewed follow the structure of "*Forward Theory*" GIS approach, as highlighted in Figure 4.2a. Within this approach, model parameters are selected, a model created and the suitability of locations for development are predicted. As previously noted, however, such approaches are highly sensitive to assumptions in defining the weighting of parameters.

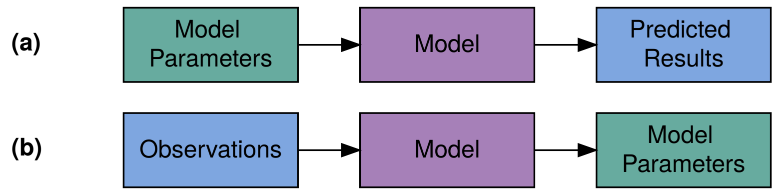


Figure 4.2: Comparison of Forward and Inverse GIS MCDA model structures.

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 (Cirucci, 2014). This approach is outlined in Figure 4.2b. Although retrospective techniques have not been applied to the field of wind energy, they are examples of analysis conducted in public health studies (Brody et al., 2002; Garcia-Ayllon, 2013; Mohamed et al., 2004; Yamada et al., 2009) and infrastructure location decision-making (Cirucci et al., 2015; US EPA, 2002). Such an approach appears suitable for onshore wind energy in the UK, and as of 2017, there are more than 3500 onshore wind turbine applications within the UK which can be used to provide an insight into the planning outcome of projects.

Combining non-commensurate data

A further challenge arises from the standardisation of non-commensurate datasets within the MCDA process. As an example, costs can easily be calculated by aggregating the available wind resource, distance to power grids, etc. However, cost cannot be directly summed with social and environmental parameters, including the proximity to urban areas and landscape designations. Standardisation is therefore required to combine the non-commensurate datasets, and different techniques may lead to different land-use suitability patterns. In addition, there is little theoretical and empirical justification for transformations methods (Jiang & Eastman, 2000). This is discussed further within the methodology in Chapter 5.

Based on the findings of this first stage of the literature review, it was determined that a greater understanding was required of the parameters which influence the planning acceptance rates of wind energy projects. The following section therefore explores the wider range of qualitative literature.

4.3 Social Acceptance Parameters

Section 4.2 presented the development of wind energy site selection studies. These studies have largely developed using the geospatial parameters outlined within Section 3.3, including wind speed, distance to urban areas etc. However, literature has suggested that there may be a wider range of parameters that should be considered, and that the acceptability of wind energy projects is based on more than just geospatial parameters (Horst & Toke, 2010). To this effect, it has been noted that public acceptance of wind energy "*has gone from a marginal and little studied point of discussion to be at the forefront of broader debates in the social sciences*" (Fournis & Fortin, 2017).

This section of the literature review builds upon the existing geospatial literature MCDA presented, and identify the broader social, institutional and psycho-social influences which relate to wind energy planning acceptance. This section is formed of three key parts:

1. **Acceptance Parameters for Onshore Wind**: identifies parameters that have been suggested to be connected to the acceptance of wind energy projects.
2. **Qualitative Assessments**: explores the use of surveys to assess the relationship between broader social parameters and wind energy projects.
3. **Quantitative Analysis of Wind Energy Acceptance Rates**: explores the use of statistical techniques to identify relationships between parameters and planning acceptance rates.

As highlighted in Figure 4.3, the three separate parts of this section form three distinct parts within the approach. Literature is first reviewed to identify potentially influential parameters. Qualitative assessments can then be used to form hypotheses, and then the resulting hypotheses can be tested using quantitative methods. This section is structured thematically around these three key points.

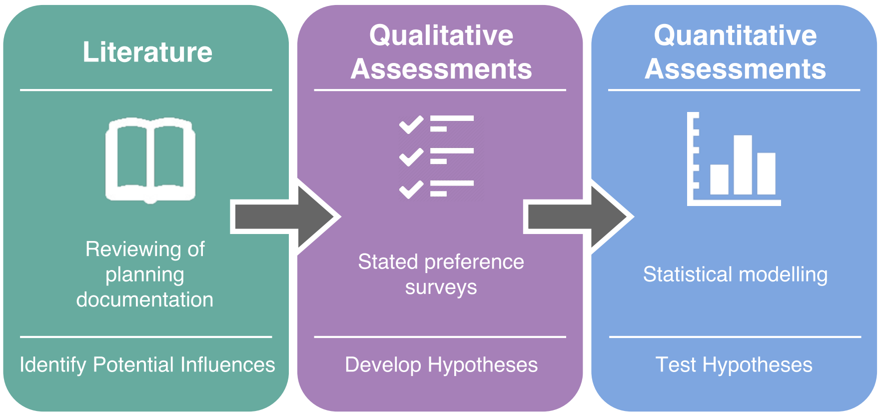


Figure 4.3: Process of identifying key parameters to be used within the analysis.

4.3.1 Scope of Literature Search

Compared to the literature review of GIS-MCDA, which aimed to catalogue all recent developments, the aim of this section is to capture the main research trends and developments. As such, only the key research papers are provided within each of the subsections.

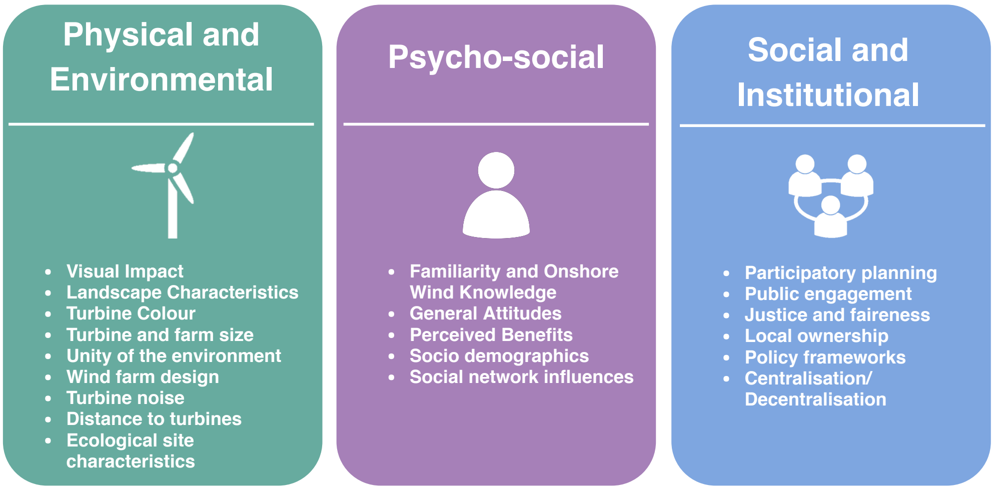


Figure 4.4: A summary of factors that influence the social acceptance of wind energy projects. Information adapted from Langer (2016).

For the qualitative approaches, the review primarily focuses on the use of stated-preference surveys. The review does not seek to explore the exact application of the techniques, but is primarily focussed on understanding the conclusions drawn from the studies, and the inferred connections between wind energy planning acceptance and the parameters outlined in Section 4.3.2.

For the review of quantitative literature, the scope primarily focussed on the use of statistical regression techniques to measure the influential parameters. However, the detailed discussion of these techniques is not included within this part of the literature.

4.3.2 Acceptance Parameters for Onshore Wind

Before further exploring the issue of social acceptance, it is important to define the concept of social acceptance. Whilst a number of definitions are generally defined, the definition adopted for the purpose of this report is:

> "a favourable or positive response (including attitude, intention, behaviour and - where appropriate - use) relating to proposed or in situ technology or social technical system by members of a given social unit (country or region, community or town and household, organisation)" (Upham et al., 2015, p. 107).

It is generally supported that geographical variables such as quantity of wind resources are in themselves insufficient to explain patterns of implementation of wind power (Horst & Toke, 2010; Langer et al., 2016; Toke et al., 2008). A critical review of the key parameters is provided by Langer (2016), which examined 146 journal articles relating to public acceptance, perception and attitudes towards onshore wind turbines. This analysis highlighted the key categories and parameters that have been connected to the acceptance rates of wind energy projects, as highlighted within Figure 4.4. These sections are expanded upon within the following subsections.

Physical Characteristics

Visual impact has been considered the main influence on public attitudes towards wind farms, as "*aesthetic perceptions, both positive and negative, are the strongest single influence on public attitudes*" (Wolsink, 2000). The perceived impact on landscape seems to be the crucial factor in this regard, and opposition to the visual despoliation of valued landscapes has been analysed as the key motivation to opposition to wind farms (Warren et al., 2005).

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 (Devine-Wright, 2005b; Warren et al., 2005). 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 residing away from turbines (Krohn & Damborg, 1999). 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 (Eltham et al., 2008). However, several studies have reported the opposite relationship (Ladenburg & Dubgaard, 2006; Meyerhoff et al., 2010), with the studies finding that negative perceptions increased with proximity to wind energy developments.

The wind farm size has also been indicated as a potentially important factor in public acceptance. In an international comparison of projects within the UK, Denmark, The Netherlands and Ireland, it was found that there is a systematic preference for smaller groups of turbines over large-scale installations (Devine-Wright, 2005b).

Psycho-social

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 (Langer et al., 2016). The effects of socio-demographic variables on individuals' views of wind farms have also been studied within literature (Devine-Wright, 2005b; Warren & McFadyen, 2010). 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 (Wustenhagen et al., 2007).

At an individual level, empirical findings suggest that political beliefs are correlated with social acceptance of different low carbon technologies (Devine-Wright, 2007). 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 (Populus, 2005).

Social and Institutional

It was highlighted in Section 2.5 that the planning of wind energy projects is controlled by Local Planning Authorities, who have the right to grant or refuse planning based on their local considerations. There is also the further complication that LPAs are represented by the political party in power for that local authority. It is not fully understood how these national party agendas influence local decision-making, and it has been noted that it is difficult to capture such factors within a quantitative study (McLaren Loring, 2007). To the authors' knowledge, no academic study has assessed whether the acceptance rates of onshore wind energy projects are impacted by the political mix of the surrounding area, but it seems to be an important consideration to understand given the vastly different planning rates.

It has been noted previously in this report that the UK has attempted to drive the development of renewable energy by providing support to the incumbent large-scale electricity generators, with both the NFFO and RO policies providing support to this group. This has led to a top-down imposition of projects, with little local involvement. This approach can create strong hostility from the local communities against the local project, and is suggested to be very unlikely that this is the best of models to follow (Walker et al., 2007). As noted by Toke (2008):

> "The local environmental disadvantages of wind power can lead to a lack of public acceptance of wind farms. Local ownership of wind turbines (local farmers, co-operatives or companies) can ensure local acceptance of projects"

In contrast to the UK, other European countries have encouraged greater levels of local engagement for wind energy projects. Most notably, Germany has over 60% of projects owned by community groups and local farmers. Three studies were identified which indicate that greater community involvement increases the success rates of projects, and a greater number of projects receiving planning permission for development (Eltham et al., 2008; Firestone et al., 2015; Krohn & Damborg, 1999).

4.3.3 Qualitative Assessment of Wind Energy Acceptance Rates

The literature presented in Section 4.3.2 highlighted that the issues surrounding the suitability of wind farm projects are far broader than just geospatial parameters. As such, it appears that existing modelling techniques are excluding key information when considering the suitability of sites for development. This subsection of the literature review therefore aims to explore the use of qualitative research methods to assess the influence of parameters on the public perception of wind energy projects.

This subsection focuses on the use of stated-preference surveys, which have seen increased use within the modelling of renewable energy technologies and assessing the scale of perceived impacts of projects (Menegaki, 2012). Such approaches apply a survey-based economic technique for the valuation of non-market resources, such as environmental preservation or the impact of contamination. For example, people receive benefit from a beautiful view of a mountain, and therefore studies will aim to identify the value attached to the loss of this view.

Development of Literature

Alvarez-Farizo and Hanley (2002) were among the first who used choice experiments to understand the potential environmental impacts of onshore wind developments in Spain. The study provided alternative choice models to understand decision preference of respondents according to a number of criteria (protection of cliffs, habitat and fauna, or Protection of Landscape). It was found that a greater importance was placed by respondents on protecting habitats and fauna than for geologically-rare cliffs or protected landscapes. The study concluded that such insights could be used to minimise the social cost of wind projects.

Groothuis et al. (2008) conducted a survey to understand how personal support for wind turbines resulted in support for a proposed local project. A willingness to accept framework was used to measure the compensation required to allow wind turbines to be built within the vicinity of survey participants. From the survey results, it was suggested that support for wind developments decreases as both income and age increase. In addition, it found that people with a concern of the environment are generally more supportive of local projects, contrary to the NIMBY belief that has been extensively applied within onshore wind developments.

Dimitropolous and Kontoleon (2009) examined the local acceptance of wind farms on the Greek islands Naxos and Skyros using choice surveys. On Naxos, three wind farms (each with a capacity of 36MW) were proposed while the analysis of Skyros considered ten sites totalling 333MW. The choice attributes were 1) *number of turbines* 2) *turbine height* 3) *conservation status of the site* 4) *whether planning will be carried out in cooperation with municipal authorities and local representatives* and 5) *the annual subsidy received per household as compensation for the negative externalities*. It was found that respondents valued the conservation status and a cooperative planning procedure more than the number of turbines or their height.

Krueger (2011) conducted a study in Delaware, US, to assess the social value of visual impacts from offshore wind projects. A stated preference survey was used to estimate the external costs of wind by comparing the relative acceptability of alternative proposals. The study highlighted a clear preference for wind farms to be located far away from the coast (i.e. out of sight), and also linked a number of demographic variables with the response, including 1) *gender* and 2) *education*, finding that male respondents and postgraduate degree students appeared generally less supportive than the general population. While the study considered offshore technologies, the findings were considered to be of relevance for potential onshore developments.

Jones (2011) studied the connection between local demographics and the view on wind energy. The survey assessed the view of wind development against a range of variables including 1) *age*; 2) *gender*; 3) *length of residency in the region*; 4) *employment status*; 5) *home-ownership*; 6) *past or current affiliation to the energy industry*; and 7) *belief in anthropogenic climate change*. The study concluded that age was as a significant predictor of capacity estimates, such that the older people were, the fewer turbines they would tend to endorse (Jones et al., 2011).

In addition to the review of literature outlined in Section 4.3.2, Langer et al. (2016) conducted qualitative analysis in Bavaria to identify potential influences on acceptance rates. A detailed review of literature and interviews with key stakeholders in wind energy was conducted to identify factors which appeared to have influenced the outcomes of planning. The authors conclude:

> "Looking to the future, there is a need to combine qualitative and quantitative research. Qualitative research aims to represent different views and opinions as well as to generate hypotheses. Therefore, in order to enhance knowledge about contradictory influencing factors qualitative research could uncover which conditions induce acceptance towards wind energy. In addition, quantitative research approaches on the influencing factors on acceptance of wind energy would enrich insights by analyzing a representative sample. (Langer et al., 2016, p. 256)"

4.3.4 Quantitative Analysis of Wind Energy Acceptance Rates

As noted by Langer et al. (2016), there is the need to combine qualitative and quantitative research to identify which conditions induce acceptance towards wind energy. Whilst qualitative research is primarily exploratory in nature, quantitative research can be used to quantify the problem by way of generating numerical data or data that can be transformed into usable statistics.

5 studies were identified which utilised quantitative techniques to assess the social acceptability of onshore wind energy projects. A summary of these studies is presented in Table 4.3, and is discussed further within the following subsection.

Several regression techniques were used within the studies, including multiple linear regression, logistic regression and probit regression. Linear regression models are suitable for assessing the relationship to *continuous* outcome variable, while logistic and probit regression are suitable in cases where there is a *binary* outcome (i.e. yes/no). There are only minor differences between logistic and probit regression, specifically how the distribution of errors is assumed. However results broadly tend to be similar.

Table 4.3: A summary of the quantitative studies completed assessing wind energy acceptance rates reviewed within the literature.

ID	Study	Country	Statistical.Method	Scope
4	(Van Rensburg et al., 2015)	Ireland	Probit Regression	Technological Institutional
3	(Van der Horst and Toke, 2010)	Scotland	Univariate Regression	Socio demographic
2	(Haggett and Toke, 2008)	England and Wales	Logistic Regression Discourse Analysis	Logistic Regression; Discourse Analysis & Key actors
1	(Toke, 2005)	England and Wales	Logistic Regression	Key actors

Development of Literature

Toke (2005) 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. In particular, it was noted that there was specific concern on the impact of projects on the economic impact on a region, either through loss in property value or tourism revenue.

Haggett and Toke (2008) reapplied the analysis applied by Toke (2005) to include Discourse Analysis (DA) to further understand issues in public administration, and further consider how campaigns handle accusations of 'Not In My Back Yard' (NIMBY-ism). The work is novel for its combination of qualitative and quantitative analysis, and highlighted the benefit of analysis that included both forms.

Van der Horst and Toke (2010) 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 (of which 40 were approved). Univariate regression analysis was conducted with the Mann-Whitney test being used to analyse the associations between the dependent variable (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 appear to generally be more likely to receive planning permission in deprived areas, and as previously noted within the review, some developers were "*keen to avoid relatively privileged communities and target areas where people are thought to less likely put up a fight*" (Horst & Toke, 2010, p. 220). These issues highlight the potential importance of social parameters in site selection.

Van Rensburg et al. (2015) 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 counters the views reported within many previous studies. Of the variables included within the model, it concluded a 0.31 predictive confidence value (i.e. it was able to account for 31% of the variance within planning outcome decisions).

[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.

4.3.5 Critique of Planning Acceptance Literature

This section highlights the wider range of parameters which have been linked to the planning acceptance of wind energy planning applications. It has been demonstrated that a broad range of physical, psycho-social, social and institutional factors are connected with the public acceptance of wind energy. However, such parameters are largely excluded from existing geospatial modelling techniques and therefore there is a clear gap in the suitability of such techniques.

There has been a growth in both the use of qualitative and quantitative research techniques to assess the level of influence parameters have on planning acceptance of wind energy projects. The analysis presented by Van Rensburg et al. (2015) highlighted the effectiveness of using regression analysis to identify variables which significantly impact planning acceptance, and valuing their relative importance. The outcomes gained from such models can provide useful insights to planners and developers alike to understand and locate turbines within suitable sites. However, a number of limitations can be identified within the context of this thesis:

1. **Consideration of Geospatial Parameters**: the study did not consider many of the physical parameters which were indicated as potentially influential within both Sections 4.3.2 and 3.2. Models are largely built around the assumption that the proximity to "*sensitive*' features (i.e. urban areas, landscape designations, airports) lessens the suitability of a potential site.
2. **Difference in Study Region**: the study was conducted within the context of Ireland. As previously indicated, there are national differences between the social acceptance of wind energy projects in different countries and landscapes. It is therefore argued that the findings of this study cannot be directly utilised within modelling within the United Kingdom.

To the author's knowledge, there has been no attempt to combine the results of quantitative studies in onshore wind with traditional GIS-MCDA methodologies. Such an approach responds to comments from Van der Horst and Toke (2010), who noted that the limitations in applying their results is that they have focused on the planning approval aspect rather than the site selection decision. They note that such future analysis could be relevant to address developer concerns about identifying appropriate sites.

4.4 Energy & Scale

The third aspect of the literature review focuses on the issue of planning scale within energy planning and development. As highlighted in the background information, the planning scale is a crucial question within the development of energy policy. However, existing governmental studies have been conducted at predetermined scales set by the governmental structure of the time, and it was shown in Section 2.5 that this has included RDA and LEP regions.

Having established the political drivers for the importance of spatial scale within Chapter 2, the primary focus of this literature review is to identify techniques that can be used to assess spatial scale within energy modelling. However, the broader concepts of energy modelling are first explained in order to position the work within the field.

4.4.1 Energy Model Classification

Energy system models are frequently used to aid in the decision-making process when faced by multiple development options (Jebaraj & Iniyan, 2006). Models form an essential aspect of decision-making due to to the complexity of the problems in energy systems: not only are there a wide range of technologies to be considered, but also there are multiple objectives which may be sought to be optimised, including cost and GHG emissions.

There has been extensive interest within literature of the use of energy models to determine the most economic investments and help determine which technologies should be utilised to achieve energy targets. Hall et. al (2016) conducted a detailed review of 110 academic papers on energy system modelling within the UK. In order to differentiate the approaches used within the reviewed literature, the author of this study proposed a classification schema, of which the key criteria are summarised as follows:

1. **Purpose of the model**: studies are categorised as either 1) *General* or 2) *Specific*. *General* models seek to forecast and explore future energy scenarios, whilst *Specific* models consider a focussed part of the system in isolation.
2. **Geographic coverage**: as outlined within the background literature, analysis can be conducted at varying geographic scales (*National*/*Regional*/*Local*/*Individual Project* etc.).
3. **Sectoral coverage**: considers whether the model focuses on energy sectors only, or whether the whole economy is included. Generally, econometric models include the wider economy to assess the influence of energy prices on production.
4. **The time horizon**: there is no set definition of the timeframe, but models typically are considered *Short* (less than 5 years), *Medium* (5 - 15 years) or *Long term* (over 15 years).
5. **The time step**: the time resolution of the model,and the extent to which variability of energy supply is considered. Long-term forecasting models have typically assessed in *annual* or *five-year* timesteps, whilst smaller timesteps (*quarterly*, *daily*, *hourly*) have become more common in short-term models to attempt to account for the intermittency of renewable energy resources.

6. **Renewable Technology Inclusion**: the renewable energy technologies are included within the study, as specified in Section 2.5.
7. **Storage Technology Inclusion**: the storage technologies considered, including established technologies such as pumped-hydro storage, and more recent technologies such as batteries and compressed air.
8. **Demand Characteristic Inclusion**: the energy demand sectors included (*electricity*/*heating*/*transport*) and the type of customers (*domestic*/*industrial*)
9. **The Underlying Methodology**: There are a diverse range of *analytic approaches* applied, including econometric, accounting models, optimisation and multi-criteria models as discussed within Section 4.2.
10. **The Mathematical Approach**: mathematical approach defines the underlying programming approach taken in the model. The most common approaches are linear, mixed-integer and dynamic programming.
11. **Data Requirements**: all energy systems models require some input of data. This field attempts to specify the level of data that is necessary for each model.

4.4.2 Modelling Techniques

It is noted that within the review conducted by Hall et al. (2016), there are three methodologies which are prevalent within existing studies: 1) *Long range Energy Alternatives Planning System* (LEAP) (Heaps, 2008); 2) *MARKAL/TIMES* (Loulou et al., 2004) and 3) *MESSAGE*. Of the 110 papers, these approaches were used 80 times. However, they largely focus on accounting/macro-economic perspective, and therefore are of limited applicability within the context of this literature review. As will be discussed in the following subsection, the review focuses on geospatial-based modelling techniques and their assessment of renewable energy technologies.

Geospatial modelling techniques have been discussed in detail within in Section 4.2 to identify suitable sites for onshore wind site selection. These studies primarily dealt with the issues of energy supply in isolation, and made no attempt to compare the geospatial patterns against existing energy demand. This issue is reflected as a common challenge within the geospatial modelling of renewable energy potential, as it is argued within literature that the location of sites for renewable energy development is implicitly linked to existing energy demand patterns (Resch et al., 2014).

It can be observed that there were limited applications of geospatial models within energy modelling. In addition, it is noted that none of the papers referenced in the review explored the influence of spatial scale on energy planning, with all the referenced studies were conducted at a predetermined spatial scale (Hall & Buckley, 2016). Due to these concerns, additional literature was reviewed, focussing on geospatial modelling techniques, including those in an international context.

4.4.3 Supply & Demand Modelling

Fulfilling a regions own energy needs, termed *energy self-sufficiency*, came to prominence in the 1970s in response to the oil crisis as countries sought to reduce their reliance on foreign imports and become energy independent (Auer, 1976). A few examples have been conducted which aim to construct supply and demand models (Hulscher & Hommes, 1992; Srensen & Meibom, 1999). However, interest within these modelling approaches largely focussed at a national level, and a review of energy systems found there were few developments in the use of energy balance in determining renewable energy developments at a more localised perspective ("Optimization methods applied to renewable and sustainable energy: A review," 2011).

There have been recent developments in the use of energy balance modelling, with the application of this concept to a local level as cities or regions aim to meet their energy requirements using renewable energy technologies. A study conducted in Japan investigated the renewable energy potential compared with demand (Wang et al., 2014). Supply and demand were calculated at a resolution of 500 metres, and the net electricity balance determined for each cell. The resulting maps are highlighted in Figure 4.5, highlighting regions of high net energy demand and supply, coloured red and blue respectively.

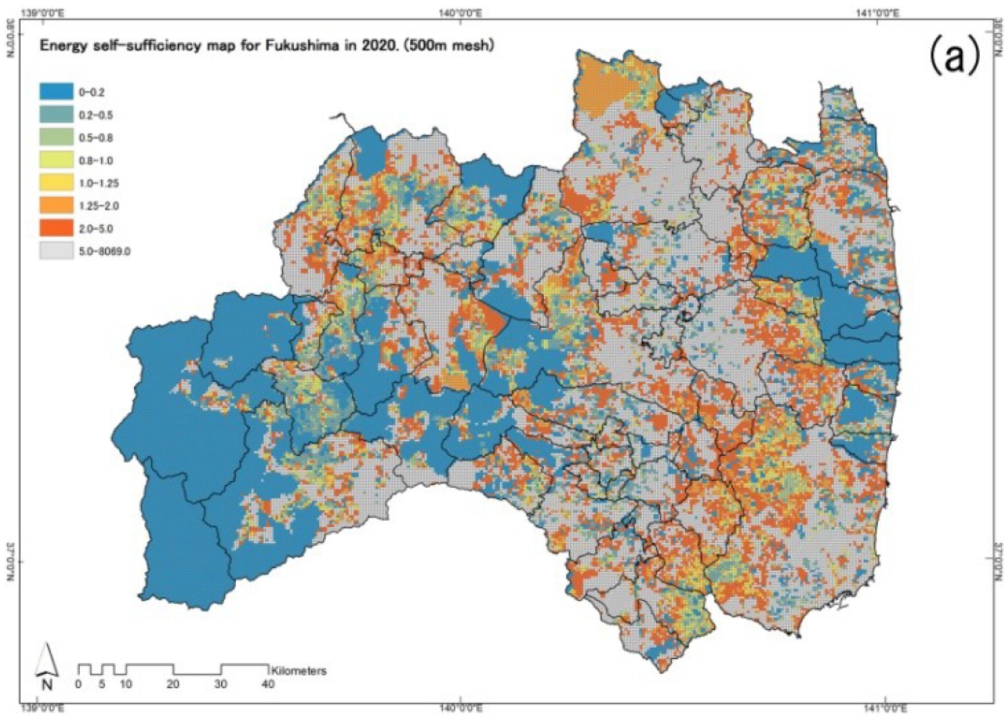


Figure 4.5: Calculation of energy self-sufficiency within methodologies (Wang et al., 2014).

The study highlighted the mismatch between rural regions (net producers) and urban regions (net consumers). By comparing supply and demand using such a method, it was noted by the author that regions could be determined which may have potential energy self-sufficiency with balanced supply and demand. However, the analysis did not go as far as undertake analysis to determine the spatial organisation.

4.4.4 Spatially Explicit Energy Models

There has been increased interest in modelling the influence of spatial scale on renewable energy target setting (Ramachandra & Shruthi, 2007). Regions are often unaware whether their regional characteristics are compatible with aspirations for energy neutrality (Balta-Ozkan et al., 2015). In addition, it is observed that targets are often set for regions on little evidence regarding technological feasibility (Oudes & Stremke, 2018).

There has been recent focus on the idea of spatially dependent renewable energy targets. A Spatial Transition Analysis (STA) methodology has been developed, whereby the regional targets vary for a region depending on their available supply and demand resource (Oudes & Stremke, 2018, p. 2). Whilst STA model presented provided an improved framework, it is argued the application of this model is different from the aim of this study. Whilst the study altered targets to meet the spatial resource of an existing region, the spatial scale of the analysis was fixed. It is instead proposed that a set target should be established, and the regional extent be varied in order for the target to be achieved, as will be explained further within Chapter 10.

There have been examples of regions which have achieved energy neutrality. Siena, Italy (Casprini, 2013) and Samso, Denmark (Waal & Stremke, 2014) are two regions within Europe which have transitioned to renewable energy technologies. However, it is observed by Oudes et al. (2018) that both these regions have low population densities, and therefore faced less difficulty in achieving their targets. Whilst more densely populated regions have set ambitious energy neutrality targets, there is significant challenge in these regions achieving them.

Although it was not within the primary scope of this literature review, the concept of spatial scale in governance was found within other disciplines. For example, the concept of "watersheds" has been explored for water resource management, whereby it is argued that the scale at which water resources are managed match the drainage basin of water bodies (Padt et al., 2014, p. 173). Such an approach is argued to encourage a more sustainable use of water resource, and more naturally reflects the "Matching Principle" discussed within Section 2.2.

4.4.5 Critique of Literature

Due to the complexity of energy modelling, there is a broad range of literature available. Whilst the topic of spatial scale has been raised in literature (Frew & Jacobson, 2016; Horsch & Brown, 2017; Oudes & Stremke, 2018), there has been limited literature regarding the assessment of the suitable planning scale of cities, and no quantitative assessments have previously been conducted.

To the author's knowledge, there is no published literature that directly assesses renewable energy planning scale. Studies have typically focussed on identifying solutions for a predetermined scale (city, regional, national, etc.) as seen in the existing GIS-MCDA models. By assessing the spatial scale of energy modelling, a greater understanding could be achieved of the scale at which optimal targets could be set. This will be explored further within Chapter 10.

4.5 Conclusion

The literature review has summarised the overall development of wind energy geospatial modelling, and highlighted the broader issues surrounding the social acceptance of wind energy projects. Finally, it was shown that there is significant amounts of literature within energy modelling, although there have been limited attempts to assess the implications of spatial scale on achieving renewable energy targets. The main limitations of the literature were therefore summarised as follows:

1. **Existing Wind Energy Models are largely based on technological concerns**:

23 studies were highlighted which assessed the suitability of a region for onshore wind development in Section 4.2. However, these studies have largely been based around technological concerns, and they appear to largely exclude the social parameters which have pose a major barrier to the development of wind energy.

2. **MCDA parameter weighting lack sufficient justification**:

The results from GIS-MCDA models are highly sensitive to the underlying modelling assumptions and the parameter weightings. Whilst AHP has been used within studies to determine these weightings, the results still remain subjective and are heavily influenced by the background of those who are surveyed. It was highlighted that an inverse GIS-MCDA approach provides a method to determine the influence of parameters non-subjectively, yet has not been applied within the context of onshore wind energy.

3. **There is limited validation of models against existing development patterns of wind energy projects**:

It was noted that 5 studies directly compare the results of onshore wind MCDA analyses again the actual development patterns of wind turbines (Aydin et al., 2010; Gass et al., 2013; Miller & Li, 2014; Van Haaren & Fthenakis, 2011; Watson & Hudson, 2015). Whilst there has been interest within literature to rigorously quantify key influences of wind energy planning acceptance from historical planning outcomes (Haggett & Toke, 2006, Horst & Toke (2010), Rensburg et al. (2015), Toke et al. (2008)), these have largely focussed on institutional parameters instead of geospatial characteristics. In addition, the findings from such studies has yet to be integrated within a full geospatial model.

4. **Limited development of spatially explicit energy models**:

It was demonstrated in Section 2.2 that spatial scale is a key consideration within the modelling of renewable energy. However, there has been limited research to assess the influence of this on regional target setting for renewable energy, with only one study being identified which explores the influence of spatial scale on energy transition targets (Oudes & Stremke, 2018). Compared to existing studies, it is argued that spatial scale should be considered as a variable within the analysis, not assumed to be optimal.

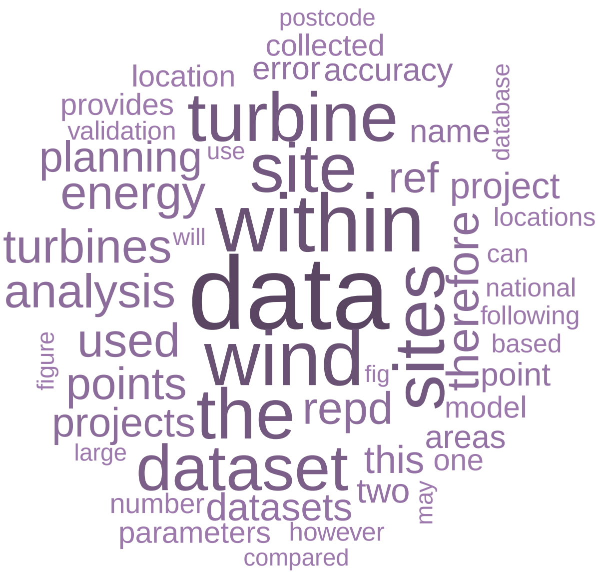
Chapter 5 builds upon these limitations of existing literature, and outlines the overall methodology of the research project. In doing so, the chapter aims to highlight how the concerns are addressed within the work.

Chapter Summary

- An extensive review of geospatial modelling approaches was conducted, with 23 international studies identified within the scope
- GIS models primarily focus on technical issues, with high emphasis frequently placed on the wind resource.
- There is often limited justification provided for the weighting used within MCDA. Whilst AHP techniques are occasionally used to overcome these concerns, this technique remains highly subjective.
- Section 4.3 highlighted that the planning acceptance of wind energy projects is influenced by the physical characteristics of the site, psycho-social, social and institutional factors.
- There has been increased interested in using qualitative and quantitative methods to identify influential parameters for the planning acceptance of onshore wind projects.
- To the author's knowledge, no studies have considered spatial scale explicitly within the analysis.

Part II

Analysis Preparation



The aim of this section is to outline the overall methodology of the research project, and prepare the required datasets into a suitable format for the statistical analysis presented in Part III.

- **Chapter 5** details the overall research methodology, highlighting how the study aimed to address the gaps identified within existing literature.
- **Chapter 6** details the wind energy project dataset used within the analysis that provides the planning and spatial data. A key part of this chapter highlights the validation process, which was conducted to assess the locational accuracy of the turbine data used within the model.
- **Chapter 7** explains the data sources used within the statistical analysis, and the process used to standardise these datasets. The datasets are spatially joined to the wind energy dataset, allowing for their use within the analysis presented in the following chapters.

Chapter 5

Research Methodology

Part I of the thesis highlighted the research context of the project, and identified a number of key issues surrounding renewable energy development. Building upon these limitations with existing methodologies, this Chapter presents the overall research methodology and explains the key stages of the analysis.

5.1 Research Approach

The research is broadly split into five key phases:

1. **Wind Turbine Data Preparation**: wind turbine data is collected and formatted for use within the analysis. A validation process is made to ensure the locational accuracy of the dataset and ensure it is suitable for use within the later stages of analysis.
2. **Contextual Data Collection**: The research involves the collation and processing of data compiled from a range of sources. This explains the steps taken to ensure sufficient data accuracy and preliminary research to explore potential indicators within the datasets.
3. **Statistical Analysis of Turbine Planning Acceptance** A large number of GIS-MCDA models have been previously developed, which utilise a range of geospatial parameters to identify suitable sites for wind turbine development. However, these models often lack validation of their input assumptions, and as a result, concerns have been raised regarding their validity. This section presents statistical analysis which analyses the location of existing wind turbines.
4. **Onshore Wind GIS-MCDA**: Combining the results from the first stage of the analysis, a GIS-MCDA was built which integrated planning, social and econometric constraints to identify potential suitable sites for wind turbine developments.
5. **Energy Spatial Scale Assessment**: Existing electricity capacity methodologies have been conducted at a specified scale or region. However, this ignores the challenge faced by cities,

which need to have a greater understanding of the area required for them to potentially meet their electricity demand. The third stage of the analysis therefore seeks to apply energy clustering principles to understand the optimum sized region at which urban and city energy demand can be met.

A summary of these analysis stages is shown in Figure 5.1. This flowchart is also presented at the start of each Chapter, highlighting the data sources and process used within the Chapter. A distinction is made between "Data" which represents a single datasets, and "Database", which are aggregated datasets representing multiple different attributes.

Study Scope

The study was conducted across Great Britain (England, Scotland & Wales). This was chosen because of the broadly similar categorisation of land types, nature designation, data availability and legislation across these regions (HM Government, 2014). The Shetland Islands had initially been included within the scope of the analysis; however, it was considered that their geographic isolation and distance from mainland Britain created issues in generalising the model results.

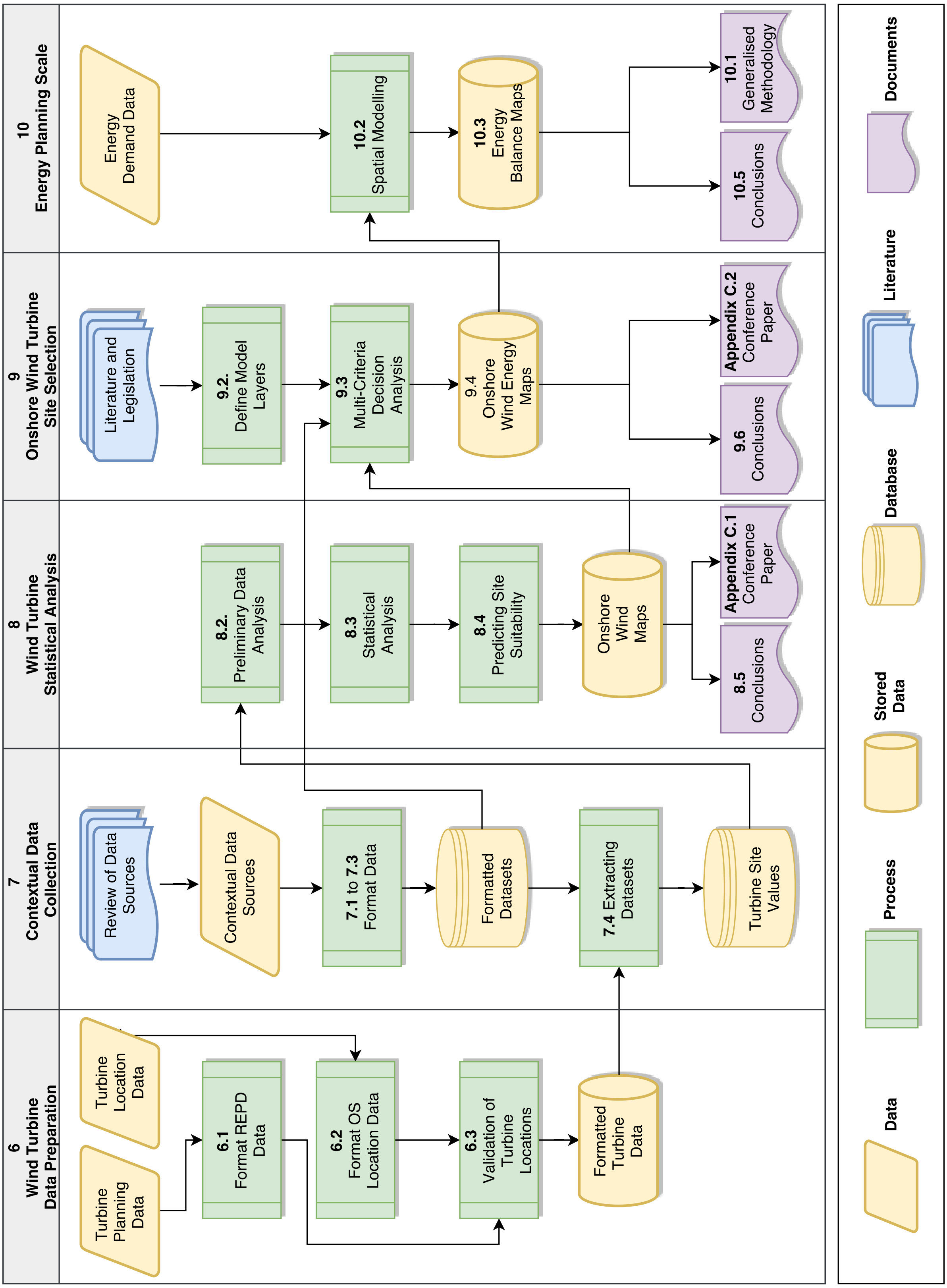
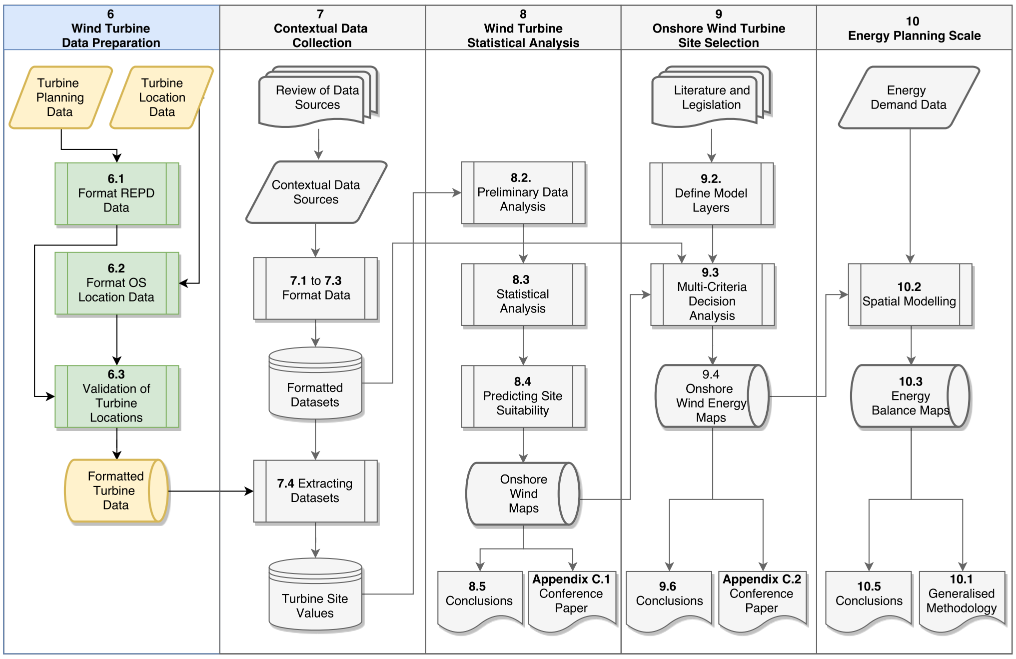


Figure 5.1: Summary Schematic for Research Methodology.

Chapter 6

Wind Turbine Data Preparation



The location of wind energy project planning applications is central to the modelling and analysis conducted. The overall aim of this chapter is to explain the data collection and processing implemented to prepare the wind turbine data for the analysis, and is broken into the following objectives:

- to explain the data sources used for wind energy project positional data in the UK.
- to reformat datasets to prepare for use within the analysis.
- to validate the positional accuracy of the wind turbines within the dataset.
- to quantify potential error within the dataset.

6.1 Turbine Location Data

Data for wind energy planning applications was extracted from the Renewable Energy Planning Database (REPD), which records commercial wind energy planning applications since 1990 (DECC, 2016c). The information for each planning application includes 1) *project attribute data* (number of turbines, capacity); 2) *year of the project planning*; 3) *planning application decision*; 4) *registered address of the project* and 5) *site coordinates*.

Whilst data has been recorded since 1990 within the REPD, there was a change in the methodology used to record projects in 2014. The changes increased the minimum size of a project which was recorded from 0.1 to 1MW, reflecting the general increase in size of commercial-scale projects which has occurred due to advances in technology. Data was therefore collected from two separate datasets:

1. **Latest REPD Release**: the data released monthly. Includes information on all planned projects larger than 1MW. The dataset used within the analysis was last updated on 04/08/2017.
2. **Archived Release**: The method of data collection changed in October 2014, and before this date all projects greater than 0.1MW in size were recorded. This therefore also provides data of the smaller wind energy projects (between 0.1MW and 1MW) constructed from 1990 to 2014.[1]

For comparison, Figure 6.1 highlights typical sizes of wind turbines and power outputs. As the REPD records the *project size*, the latest release of the REPD dataset includes 258 where the turbine is less than 1MW, but multiple turbines are installed.

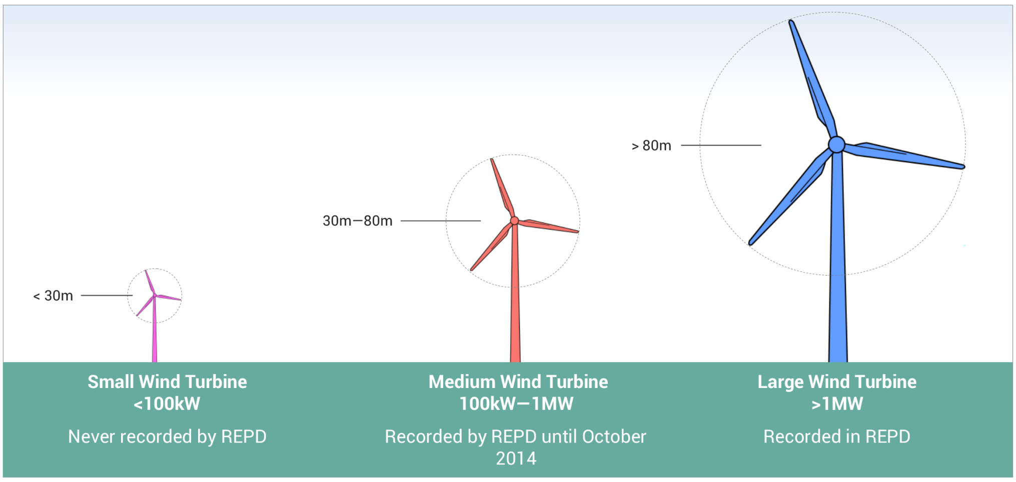


Figure 6.1: Comparison of Wind Turbine Size categories, indicating whether they are included within the REPD dataset used in the study.

[1] It should be noted that any wind energy developments smaller than 1MW proposed since October 2014 will not be included, however these were deemed to be insignificant as the size of turbines has increased and most commercial projects are now greater than 1MW.

The database records the latest planning application status of the project, which is updated to reflect any changes to the project development. 12 different stages are included within the database, with Figure 6.2 highlighting the potential pathways which can be followed by projects. Turbines with a hub height of less than 12 metres do not require planning, although such sized turbines are not recorded within the dataset due to their size. For other projects, there is a process of application, for which the decision is granted or refused. Projects which are refused can optionally be taken to appeal by the developer, or alternatively abandoned.

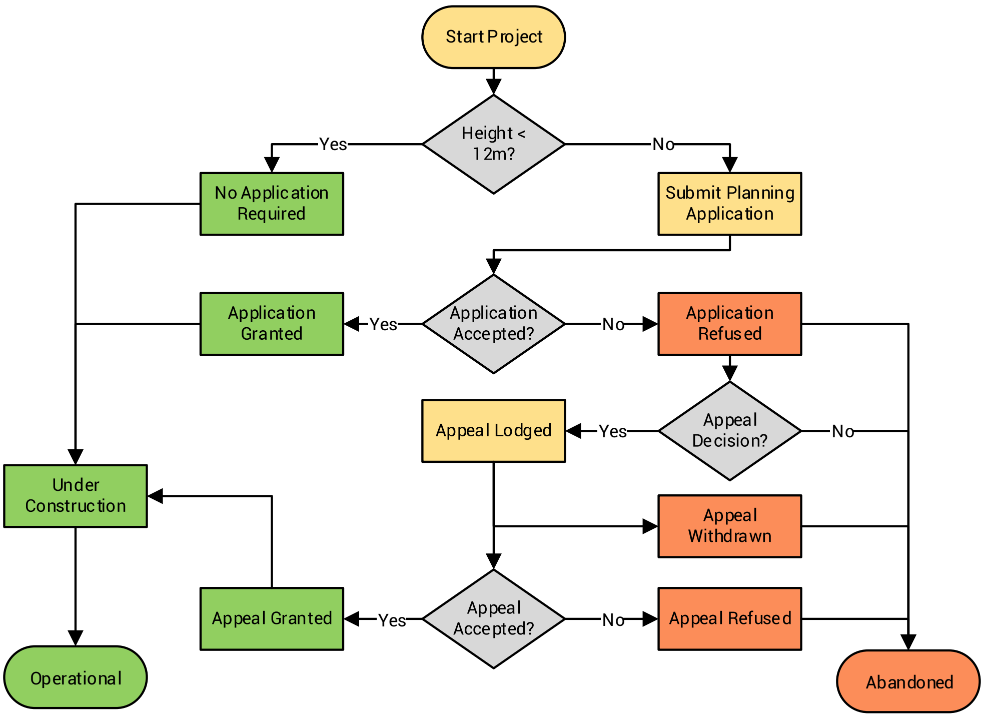


Figure 6.2: Potential planning pathways for a wind turbine application.

6.1.1 Processing Wind Energy Project Dataset

The REPD data provides information for all renewable energy technologies developed within the UK, with more than 12000 projects recorded. Several measures were therefore taken to prepare the data for analysis, as follows:

1. **Filter data to onshore wind energy only**: the database provides information on all renewable energy technologies.
2. **Filter to Study Region**: as previously mentioned, the study scope was selected to cover Great Britain only, and therefore wind energy projects from Northern Ireland were excluded.
3. **Summarise Planning Status**: The planning status for each site was summarised into 3 status categories *(Accepted/Undecided/Rejected)*.
4. **Add a database key to each record**: this allows records to be easily identified
5. **Remove superfluous variables**: The data included many unneeded values for onshore wind energy which only apply to other renewable energy technologies.

6. **Adjust Coordinate**: The coordinates had to be reformatted to be suitable for geospatial analysis. Primarily, commas within the variable had to be removed, and the resulting character string was converted to a numeric variable.
7. **Impute Missing Year**: a portion of planning applications were missing the variable *"year"*. Upon inspection, it was found the record *"Date last updated"* were typically to be similar in value to the application date. This value was therefore used to impute the value.
8. **Correct for inconsistencies between the datasets**: differing naming conventions are used for the variables between the recent and historical datasets.
9. **Merge the datasets**: finally, the two REPD datasets were merged into a single dataset.

The final dataset included 1809 wind energy projects between 0.1 and 1MW, and 1780 projects with a capacity greater than 1MW. This represents the overall site capacity, not the individual size of each turbine.

The dataset includes projects that are in one of three main stages: 1) *Approved* 2) *Submitted (In Planning)* 3) *Rejected/Abandoned*. In order to conduct the statistical analysis presented in Chapter 8, the planning status must be reduced to a dichotomous variable. This was achieved by removing the projects within planning and producing a dataset which represents either Accept (1) or Reject (0). This filtering of data reduced the number of projects from 3589 to 3100 entries.

Using the longitude and latitude data provided within the REPD, the data was projected to provide a geographical reference for each site. The complete wind energy dataset is shown in Figure 6.3, with the data faceted by the planning status.

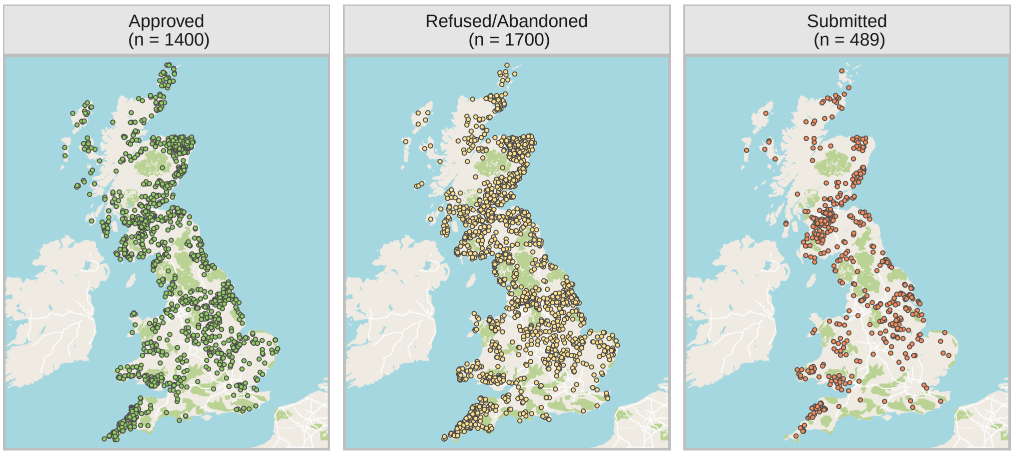


Figure 6.3: Wind energy sites plotted by planning status summary. A count n is provided for each type of project.

6.2 Constructed Turbine Locations

Although an Onshore Wind Turbine must intrinsically be onshore, the spatial projection of data indicated that 27 were outside the extent of the coastline of Britain. This issue raised concerns of the positional accuracy of the dataset, and it was therefore decided that the REPD values should be validated against a second dataset. This section therefore explains the collection and processing of this dataset for use within the analysis.

6.2.1 Comparison Dataset

Wind turbine locations were extracted from the Ordnance Survey Points of Interest (POI) dataset (Ordnance Survey, 2016a), accessed through the Edina Digimap portal.[2] The OS POI data provides location data on wind turbines in the UK, with the location data supplied by the British Wind Energy Association. The supporting guidance states:

> "*All reported records will have meaningful grid references with turbines being absolute whilst sites will be at a reasonably central location. Turbines and sites will coexist where both have been identified. Individual turbines will have the name of the site followed by 'Turbine' whilst those instances relating just to the site itself will just report the site name*. (Ordnance Survey, 2016b, p. 5)"

Upon review, however, it was found that there were inconsistencies in the data, and that turbines could not accurately be identified based on their name as suggested. This is demonstrated in Figure 6.4, which shows that whilst all three sites were indicated as wind turbines, the middle point actually represents the site name for the project. The naming convention for the three points is also inconsistent, as the points of each wind turbine do not contain the word "Turbine" as stated. Such issues prevented it from being possible to distinguish between such points, and therefore it was required that processing was undertaken to be able to classify site and turbine points.

[2] Whilst free to use for academic purposes, the licencing prevents this data from being shared and therefore is not included within the downloadable dataset for this project.

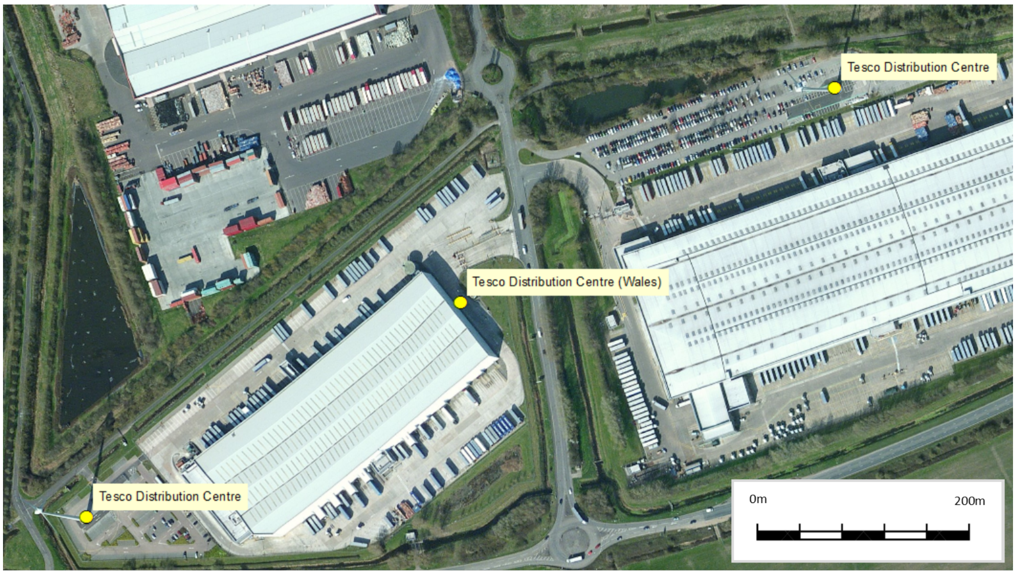


Figure 6.4: Map highlighting inconsistency in turbine naming within the OS POI dataset. Two turbines lack the turbine reference and therefore incorrectly identify as a wind farm site.

6.2.2 Classifying Turbine Sites

A methodology was developed to classify the turbine sites and turbines points within the OS dataset. As explained in the following subsections, there were two key stages to this pairing:

1. **OS POI Parameters**: additional parameters were generated for each point in the dataset.
2. **Rule-based Classification of Points**: using the additional parameters generated, the site was classified as either a 1) *turbine* or 2) *site name*.

OS POI Parameters

The following parameters were calculated for each point:

1. **Count the number of points with the same name**: if there are multiple points with the same name, it is likely that they represent turbines, whilst individual points are more likely to represent site names.
2. **Check whether the point name contains the word "Turbine"**: again, this should provide an indicator whether it is a turbine point or a site name.
3. **Check if name contain the phrase "Turbine Turbine"**: some wind farms are erroneously named "%SITE NAME% Turbine", and therefore turbines on the site are named "%SITE NAME% Turbine Turbine".
4. **Count Number of points are connected to the site name**: the word "Turbine" is subtracted from each point to see whether there are any matching points. This check was made as there were inconsistencies in the points for single turbine sites: some have only a single point while others have a point for the site and turbine.

Rule-based Classification of Points

Using the four conditions listed, a number of logic statements were used to split the data between turbine points and site data. It should be noted that these rules are not mutually exclusive, and that the same point may meet the criteria of several points:

1. **Standard Turbine Sites**: a standard turbine site will have a unique name, and at least one point that is related to it (i.e. a turbine with the same name).
2. **Standard Turbine Point**: a standard turbine point has more than one point with the same name, contains the word turbine and has no dependent points.
3. **Sites Which Contain the word "Turbine"**.
4. **Sites which match both turbine and site**: if a site is unique and has no dependent or related points.
5. **All other**: any point which does not meet any of the other four conditions. Upon inspection, these were found to be wind turbine sites.

Based on the rules specified, the turbines were allocated to sites and points subsets. Turbine sites can be identified as meeting Rules 1, 3 or 4. Turbine Points can be identified as meeting Rules 2, 4 or 5. The 5354 points were categorised into 4729 Turbine points and 802 wind turbine sites. It should be noted that 177 points have counted as both turbine and site points, resulting in an increase in the number of points.

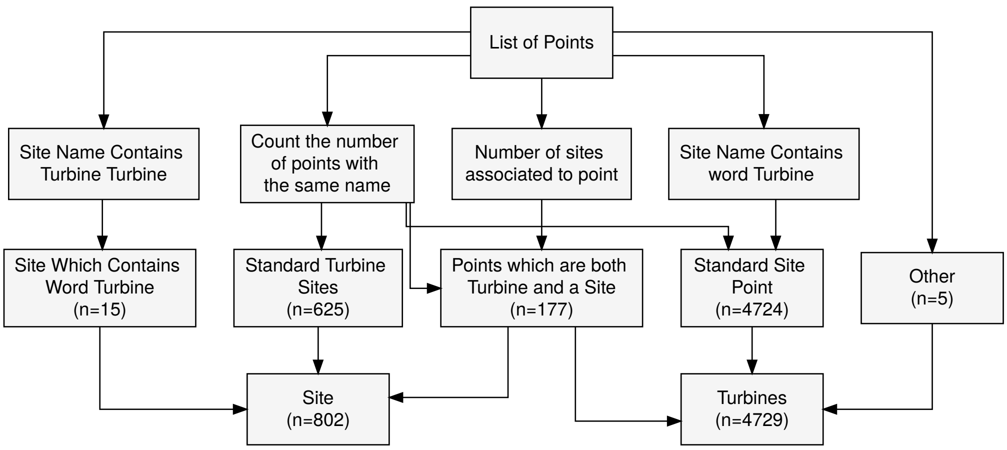


Figure 6.5: A schematic of the OS point identification algorithm. A count n is shown, highlighting the number of observations within each group.

To validate the allocation of points to the two datasets, 100 points were randomly sampled and manually compared with satellite imagery. It was found that there was 100% accuracy between the two datasets, and was deemed sufficient validation for the analysis.

6.3 Validation of Turbine Locations

The turbine planning data recorded by the REPD only provides a single point per wind farm representing the registered address of the site. It was highlighted in Section 6.2 that there were concerns surrounding the positional accuracy of these sites, and as an example, it was seen that a number of wind farms had been indicated to fall outside of the coastline of Great Britain. It was therefore determined to be important to understand the errors present in the dataset, and assess the positional accuracy of points.

Figure 6.6 highlights the inconsistency between the REPD and the exact location of constructed turbines, as provided by Ordnance Survey (OS). It can be seen that sites 1 and 2 generally are well matched, while 3 only has a small difference between the REPD and OS data sets. However, there is a difference of 1.8km between the REPD and OS data for site 4, while site 5 has no REPD record. Several potential causes of errors were hypothesised for the data:

1. **Data entry errors**: The coordinates may have been erroneously inputted into the database.
2. **Sites are defined by a single point**: The REPD database only provides a single point for the site, which is not necessarily the centroid of the development. For example, it could be the address of the registered site that may cover a large area.
3. **Postcode Inaccuracies**: The location may be based on the postcode, which can cover large areas in rural locations.

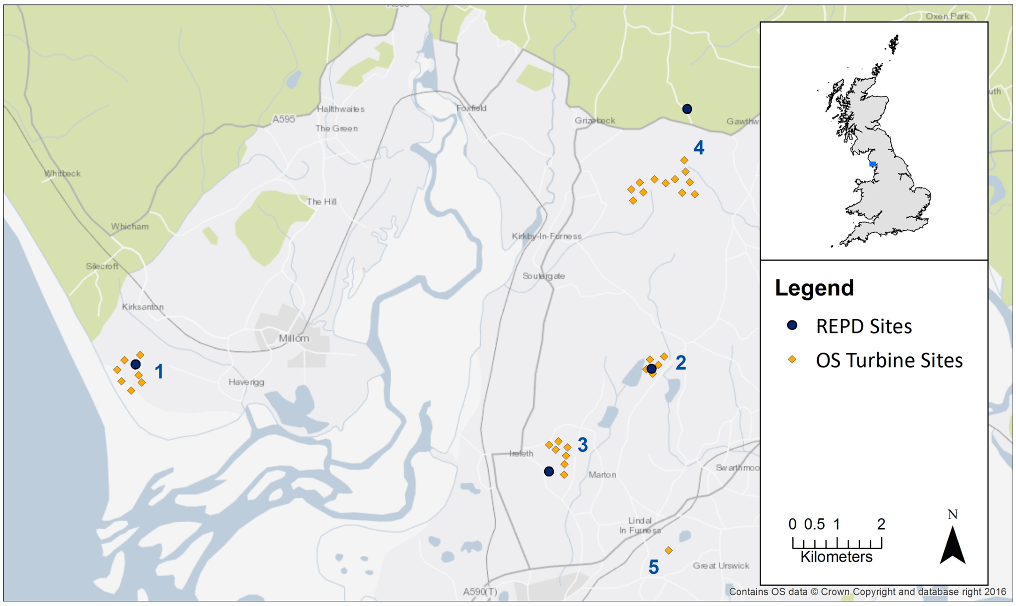


Figure 6.6: A map highlighting the geospatial inconsistencies between the OS and REPD datasets.

It was important that the inaccuracy within the turbine dataset was assessed, as project locations were used to derive the predictor variables within the statistical modelling in Chapter 8. Any inaccuracy in the locations will increase the margin of error of proximity calculations: for example, project number 4 in Figure 6.6 is located outside the national park, however, the REPD record inaccurately suggests the turbines are within it. Two forms of validation were therefore used to validate the dataset:

1. **Postcode Location Validation**: the coordinates provided within the REPD database were compared against the recorded postcode. Due to the large areas covered by postcodes in rural areas, this method provides limited accuracy but can assess *regional* inaccuracies in the dataset.
2. **OS Turbine Sites**: the location of operational wind turbines in the REPD are compared against the OS wind turbine dataset. As the OS turbines provide precise locations of the wind turbine projects, this method can assess *local* inaccuracies in the dataset.

These two approaches and results are explained within the following subsections.

6.3.1 Validation against Postcode

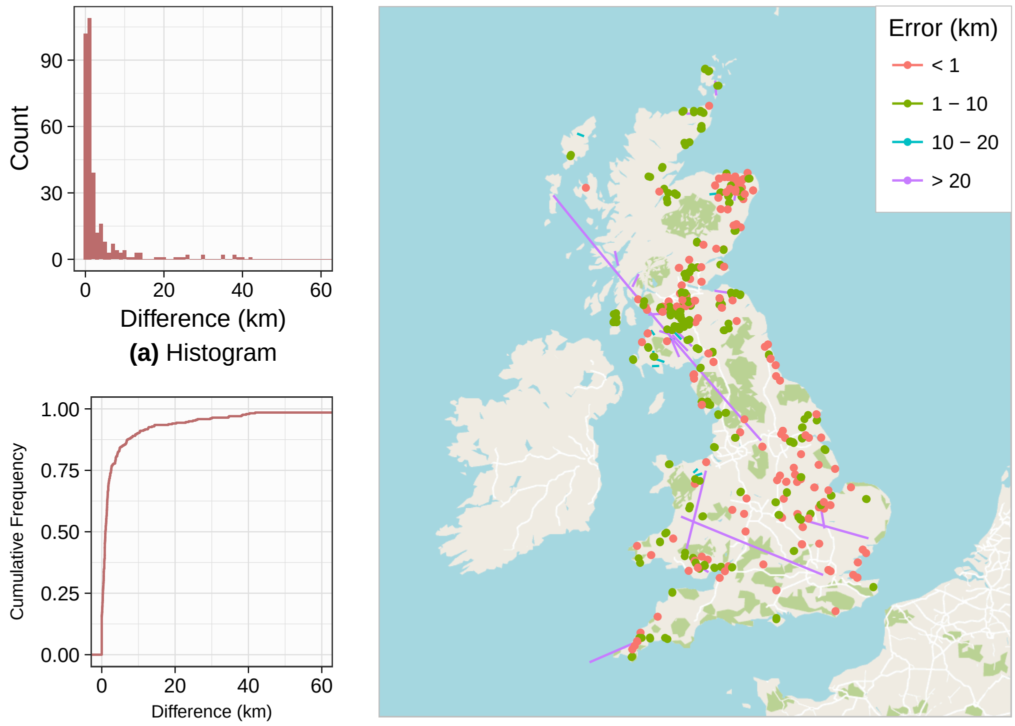
The first stage of the validation was to compare the location of REPD coordinates against the listed address. This aimed to assess *regional* level accuracy, as addresses and postcodes in rural locations often cover a large area, making it difficult to find the exact location of the wind farm. Such regional errors may have resulted from the coordinates of the site being inaccurately recorded.

The package *ggmap* (Kahle & Wickham, 2017) was used for geocoding within the analysis, as it provides an interface to the *Google Maps Geocoding API*. The geocoding searched for locations of projects that provided a postcode, which 20% have. Efforts were also made to geocode the address; however, it was found that sites largely had relatively vague names which resulted in a poor rate of success, and therefore this approach was not used: as examples, "Off A681, Bacup, Lancashire" and "approximately 4km from Ulverston". All search terms were limited to return results in the UK as some addresses were being erroneously paired to international addresses.

The results of the pairing are shown in Figure 6.7c. Lines connecting the two recorded locations for each site, termed *Error vectors*, are used to highlight the difference in locations. The mean distance between the two sets of points is 6.9km, although a median value of 1km highlights that the data is skewed by a small range of large errors, with the largest difference in being 544km.

In order to further explore the results, all sites with an error of greater than 30km were manually investigated to identify the cause of the site error. Of these 14 sites examined, it was found that 9 had errors in their coordinates being incorrectly recorded, 4 were incorrectly sited by the geocoding due to short postcodes which matched to multiple areas, and 1 had an error in the postcode whereby letters being misspelt. It is also worth noting two cases where the X and Y coordinates had been mixed, leading to them being located in the Netherlands instead of Scotland. However, these two sites were later corrected within the database.

It is also interesting to note that 15% of the geocoded sites had a perfect locational match with the postcode. This accuracy is unlikely due to be coincidence, but suggest that the coordinates of the sites may have been determined directly from the post code of the site.



(a) Histogram

(b) Cumulative Frequency

(c) Postcode Error Vectors

Figure 6.7: Results from the internal validation based on postcode matching of REPD datapoints. The histogram was truncated at 60km to remove outliers.

Having considered the anomalies within the data, the trimmed mean was calculated as 1.7 km. However, while the results provide a useful indication of model accuracy, they are of limited practical use on their own. A particular issue arises in that rural postcodes cover large areas, and therefore the site may be distant from the centroid of the postcode region. As such, this first search is best used as a regional level search to explore larger errors.

6.3.2 Validation against OS Turbine Sites

While the address validation provides an indication of potential erroneous data at a *regional* scale, it provides no validation that the site specified accurately maps at the *site-level* scale. Therefore, the positional accuracy of the planning applications was compared against locations of operational turbines as calculated from the OS Points of Interests data collected within in Section 6.2.2.

As this validation is made against operational wind turbines, it can only be used for a subset of the REPD dataset. The sites were therefore firstly filtered to only use operational wind farms within the REPD.

There was no directly comparable parameter which could be used to join the REPD and OS dataset. As a result, a process was developed to compare the two datasets and identify suitable pairings. As shown in Figure 6.8, three approaches were developed, which are explained in following paragraphs.

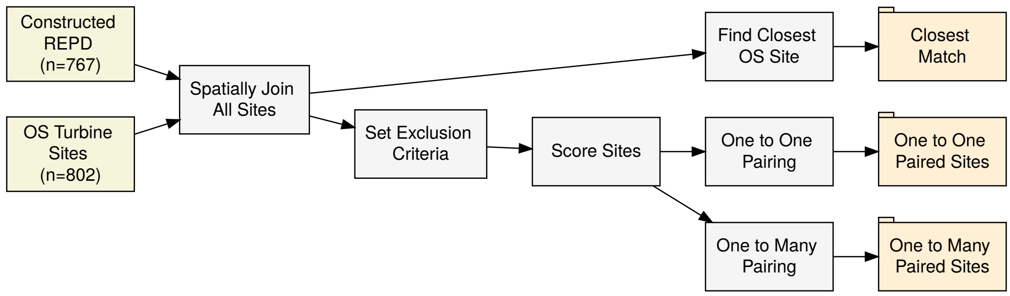


Figure 6.8: Schematic of the REPD OS pairing methodology

Firstly, a spatial join was conducted to cross tabulate the proximity of all points within the OS and REPD dataset (n = 615134). For the simple pairing approach based on the *"Closest Match"*, pairs were formed purely on the geospatial proximity of the two sites. However, there was no guarantee that these were pairing the correct sites, and upon inspection, it was found that sites were not all being paired accurately.[3]

To overcome the limitations with the *Closest Match* pairing method, additional parameters were used from each dataset to assess the suitability of the match, as follows:

1. **Site Name Difference**: A partial string match was used to assess the similarity of the OS and REPD names. The first 15 characters of each string were compared, and the differences were counted with 0 being a perfect match and 15 meaning no characters matching at all.[4]
2. **Number of turbines**: the REPD provides a count of the number of turbines on the site, and was compared with the number of turbines on the OS site as calculated within the pre-processing in Section 6.2.2.

Based on the three assessment criteria (*distance*, *site name* and *turbine count*), a filtering process was developed to remove the poorest fitting pairs within the model. This filtering process used three Boolean conditions, specifying a maximum limit for the 1) *distance between sites*, 2) *difference in site names* and 3) *Difference in the count of wind turbines*. These parameters are shown in Table 6.1, and the approach reduced the number of potential matches from 615134 to 1257.

Having filtered the potential site pairings, the most suitable sites for the reduced list were assessed in further detail. Each site was scored on the potential suitability, with the score being determined

[3]Many sites were being paired which were more than 40km away. The summary results are included within Table 6.2.

[4]The algorithm was run to not consider the order of the letters as there were slight inconsistencies in naming conventions between the two data sets which could be missed data sets may get missed (i.e "WIND TURBINE" and "TURBINE WIND" would be 0).

Table 6.1: Parameters used within the Weighted Sum Method (WSM) used to determine the most suitable OS REPD pairings.

Variable	Cut off	Unit	Parameter Weighting (w)
Distance	20	Kilometre	1
Names	13	Difference in first 10 letters	3
Turbine Number Difference	2	Number of turbines	4

using the Weighted Sum Method as follows:

$$\text{Site Suitability Score} = 3N + 4T + 1D \tag{6.1}$$

whereby N is the name score, T is the difference in Turbines, D is the site distance. The weighting parameters were derived from a trial-and-improvement method. Based on the weighting parameters shown in Table 6.1. At first, it may appear erroneous that distance was used as a parameter in the pairing algorithm, as this is the value which the model was trying to determine. However, the name and turbine count were insufficient in themselves to differentiate between the potential pairs for the REPD and OS data. To reduce the chance of the results being unfairly skewed in favour for sites with close proximity, a low weighting was applied to the distance parameter.

Once sites were scored, two alternative approaches were explored for selecting suitable pairs:

1. **One-to-one matching**: each OS can only have one REPD application joined to it. This prevents multiple projects being associated to the same REPD or OS site.
2. **One-to-many matching**: OS sites may have multiple REPD applications joined to them. This was explored as a number of OS sites have had multiple applications made at them. For example, the re-powering of an existing wind energy project would only have a single OS site while two successful REPD operations would have been made at this site. Therefore, the second match checks without a one to one relationship, matching purely on the best fitting score.

The summary statistics from the three methods are shown in Table 6.2. The "*Nearest Point*" model was able to pair for each of the REPD turbines within the model, whilst the *one-to-one* and *one-to-many* approaches only paired a subset of the points due to the filtering within the matching process. The large difference between the mean and median values highlight that there is a strong positive skew in the dataset, with only a small proportion of sites having a large error.

Table 6.2 also highlights that the one-to-one and one-to-many pairing methods have a relatively low pairing success rate. Of the 536 REPD sites, less than 60% of points were paired. The algorithm rules prioritised accuracy over coverage, and therefore no pairs would be formed for REPD sites that did not accurately match an OS site.

Table 6.2: Comparison of the One-to-one and One-to-many pairing methods.

	Number of Pairs	Mean	S.D.	Minimum	Maximum	NA
One to One	358	1.80	3.37	0.72	0	19.76
One to Many	382	2.01	3.66	0.75	0	19.79
Nearest Point	767	3.25	5.41	1.11	0	54.66

6.3.3 Error Analysis

Whilst errors were identified in the dataset, only a proportion of the sites could be validated, as each of the two approaches only dealt with a subset of the dataset. Figure 6.9 further highlights this issue, demonstrating the proportion of sites that were validated against the Postcode or OS location. It can be seen that the Postcode validation could only match 19% of sites, whilst the OS validation only analysed operational sites. As a result, 60% were not validated within the model.

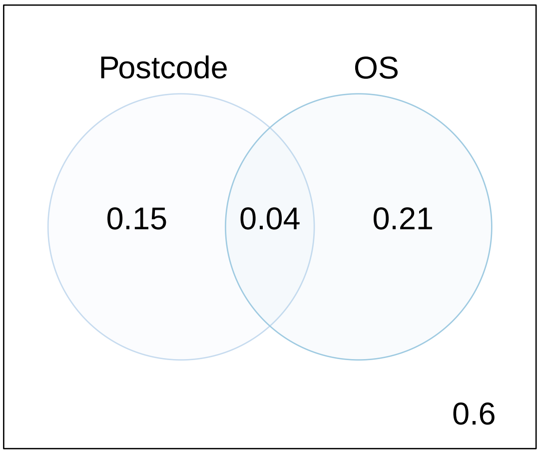


Figure 6.9: Venn diagram highlighting the matching success of the Postcode and one-to-one assessments.

Although it is known that some sites are far from their stated coordinates, there are challenges in correcting the dataset. As the OS validation could only be conducted on constructed sites, projects which have not been constructed could not be validated. Whilst it is possible to correct the known errors in the dataset, it would skew the dataset error and error would no longer be randomly distributed within the dataset. As a result, the dataset was left unadjusted, with no corrections being directly made to the dataset.

A more generalised attempt was made to identify whether there were any influences that correlated with the accuracy of the site. For example, do older sites have a lower level of accuracy compared to more recently proposed projects? To test such relationships, a regression model was developed, based on a similar approach as that outlined in Chapter 8 whereby the outcome variable (site location error) was compared against site parameters (*year of construction*, *number of turbines*, etc.). However, the results proved inconclusive, with an R^2 value of 0.17 and no statistically significant parameters identified. Due to this poor overall fit, further optimisations of this model were therefore not considered.

6.4 Conclusion

This chapter has presented the collection of wind turbine data and the measures taken to validate the suitability of the dataset for the analysis. This study used the REPD as the primary source for information and provides extensive information surrounding the planning application of each wind energy project. However, no level of accuracy was specified for the location of these sites, and therefore it was important to assess the positional accuracy of the dataset.

Two approaches were developed to validate the accuracy of the project locational accuracy. It was seen that while a small percentage of sites which had a large error, the median error from the one-to-one model is 0.72km. Although attempts were made to understand the cause of this error, no influential factor could be identified, and the error has therefore been assumed to be randomly distributed in the dataset.

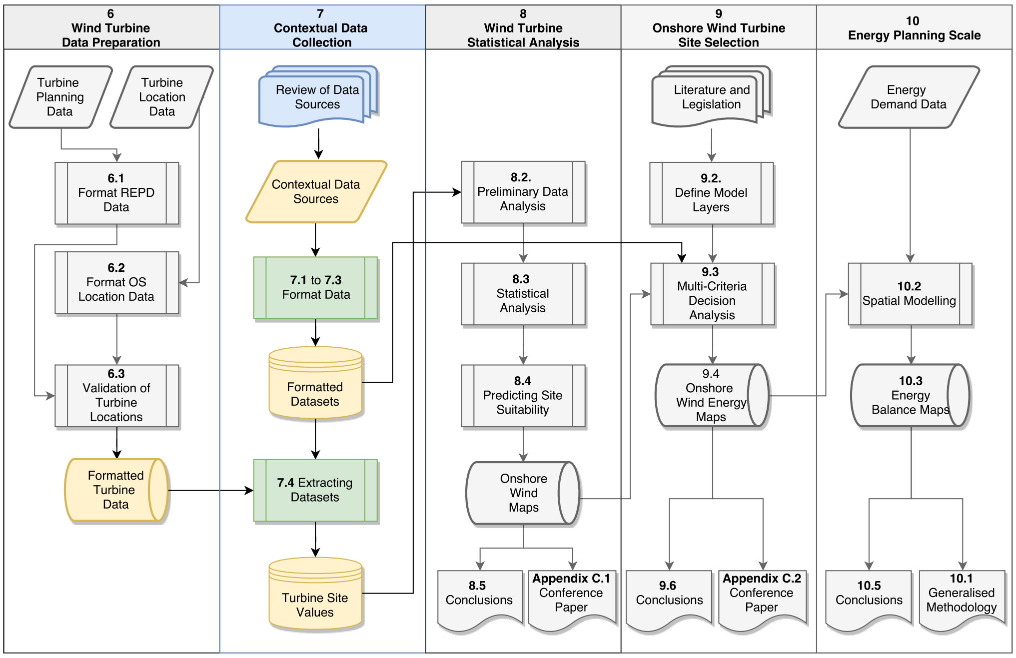
The wind energy dataset is used extensively within the following chapters and forms a key role within the geospatial modelling conducted within the thesis.

Chapter Summary

- Locations of wind energy planning applications collected from the Renewable Energy Planning Database.
- Formatting and aggregation conducted to make the data suitable for use within the statistical modelling and geospatial analysis.
- Preliminary checks indicated issues within the positional accuracy of REPD sites, and therefore site positions were validated.
- Location of constructed turbines within the UK were extracted from the OS Points of Interest Data.
- A pairing algorithm was created to match the sites between the REPD and OS datasets. Validation of wind energy data found that the median error of 0.7km.

Chapter 7

Contextual Data Collection



A range of datasets were used within the analysis, and were aggregated from multiple sources and in varying formats. This section therefore explains the processes conducted to collect the data and prepare it for use within the analysis and modelling. The section is broken into the following parts:

- to explain the overall scope and global settings used when collecting and formatting the datasets.
- to ensure the datasets were formatted correctly for analysis.
- to aggregate parameters for each wind energy project.

Table 7.1: Summary of data sources used to collect data for the study.

Category	Dataset	Region	Data.Type	Source
Turbine	Wind Turbine Planning Data	UK	Tabular	(REPD, 2017)
Resource	Wind Speed	UK	Raster	(NOABL, 2001)
Features	Roads	UK	Points	(OS Strategi, 2016)
	Railways	UK	Lines	(OS Strategi, 2016)
	Urban Areas	UK	Lines	(OS Strategi, 2016)
	Powerlines	UK	Polygons	(OS Strategi, 2016)
	HV Powerlines	UK	Lines	(OS Strategi, 2016)
	Powerlines	UK	Polygons	(Open Street Map, 2017)
	Airports	UK	Polygons	(Open Street Map, 2017)
	Military Sites	UK	Polygons	(Open Street Map, 2017)
Landscape	National Parks	UK	Polygons	(Pope, 2017)
	Heritage Coast	E	Polygons	(Natural England, 2015)
		W	Polygons	(Natural Resources Wales, 2010)
	AONB	E	Polygons	(Natural England, 2016)
		W	Polygons	(Natural Resources Wales, 2016)
	NSA	S	Polygons	(Scottish Government, 2011)
Nature	SSSI	UK	Polygons	
	SPA	UK	Polygons	(JNCC 2017)
	NNR	E	Polygons	(Natural England, 2016)
		S	Polygons	(Scottish Natural Heritage, 2017)
		W	Polygons	(Natural Resources Wales, 2010)
	SAC	UK	Tabular	(JNCC 2017)
	RAMSAR (Natura 2000)	UK	Tabular	(JNCC 2017)
Topography	Elevation	Europe	Raster	(European Commission, 2015)
Demographic	2011 Census Data	UK	Tabular	(ONS 2016)
Political	Local Election Results	UK	Tabular	(The Elections Centre, 2016)
Boundaries	Scottish Data Zones	S	Polygons	(SASPAC2011)
	Output Area Boundaries	E, W	Polygons	(UK Data Service, 2017)
	Local Unitary Authorities	UK	Polygons	(UK Data Service, 2017a)

[a] UK = United Kingdom, E = England, S = Scotland, W = Wales

7.1 Study Formation

The literature review highlighted parameters which have been connected to the acceptance rates of wind energy projects. Based on these findings, a comprehensive search was conducted to identify and collect datasets for the analysis. A summary of the data sources is presented in Table 7.1, with full explanation provided within the following subsections.

The Ordnance Survey National Grid reference system (OSGB36), otherwise known as the British National Grid (BNG), was chosen as the most suitable coordinate system for the analysis. As a projected coordinate system, it allows the use of geospatial tools which require planar coordinates in comparison to spherical coordinate systems such as WGS84.

The packages *Raster* (Hijmans, 2017), *sp* (Pebesma & Bivand, 2017), *rgeos* (Bivand & Rundel, 2017) and *rgdal* (Bivand et al., 2017) provide the fundamental tools which are used for processing the data within this chapter.

7.2 Geographic Data

This section highlights the sources of the datasets, and explains the processes conducted to standardise the datasets for use within the analysis.

7.2.1 Wind Speed

Wind speed data was collected from the Numerical Objective Analysis of Boundary Layer (NOABL) wind speed database, which provides annualised wind speed estimates at a resolution of 1km by 1km (DTI, 2001). It was derived using data from 56 stations across the UK, with an air flow model to estimate the effect of topography on wind speed (Burch & Ravenscroft, 1992). This source has been widely used by wind assessment studies conducted within the UK (Baban & Parry, 2001; SQW Energy, 2010; Watson & Hudson, 2015).

There is more detailed wind dataset which provides both monthly and annual averages along with improved accuracy (Met Office, 2014). However, this data is not publicly available and therefore was not used for the initial model. A comparison of the datasets has found that the reported windspeeds varied by 0.5m/s on average (Met Office, 2014), and therefore the NOABL database was deemed sufficient for this analysis.

7.2.2 Built Environment

The location of physical features including roads, railways and urban areas were collected from OS Strategi (Ordnance Survey, 2016b), which provides shapefile data of all main geographic features within Great Britain. Urban areas cover all types of settlements (city, towns, villages), and regions of urban areas smaller than $0.5km^2$ are not captured (Ordnance Survey, 2016b). Further to this, urban areas are captured as a large urban area if they exceed $1km^2$, and an urban area less than $1km^2$ is captured as a small urban area.

While Ordnance Survey provides many features, there is limited availability of the more detailed datasets relevant to wind energy. Therefore, Open Street Maps (OSM) was used for a number of datasets. Data was collected through the Overpass API, which allows queries to be run against OSM to extract specific features. The package *overpass* (Rudis & Lovelace, 2017) is used to directly query this API within R. The following datasets were extracted through OSM:

- **Airport data**: Ordnance Survey does not include information on smaller airfields in the UK. In comparison, OSM includes smaller airfields and military airports along with commercial airports. Each site is represented by a point as a unique identifier, and larger sites also have polygon data to mark their boundary.
- **Transmission Networks**: While data of the transmission network is available from the National Grid for high voltage (HV) powerlines, they provide a relatively limited coverage

of the regional distribution networks to which wind energy projects are typically connected. Data was therefore extracted through OSM which provided a greater level of coverage than the National Grid data, with high voltage powerline data available for 11654km compared to 7247km from the National Grid data.

- **Ministry of Defence (MOD) Sites**: Safeguarding ensures operational facilities such as aerodromes, explosive stores, radar facilities and range areas are not compromised by either onshore or offshore development (Ministry of Defence, 2014). OS Strategi does not supply details of these sites, and therefore these sites were identified in OSM.

7.2.3 Landscape and Natural Designations

Landscape designations cover a large percentage of Great Britain and restrict the developments of wind energy projects. The designations collected for the analysis were:

- **National Parks**: Areas of outstanding landscape where habitation and commercial activities are restricted (Pope, 2017).
- **Heritage Coasts**: areas which are recognised for their natural beauty, wildlife and heritage and amongst the purposes of definition is support for these qualities and enabling enjoyment of them by the public (Natural England, 2015, Natural Resources Wales (2010a)).
- **Areas of Outstanding Natural Beauty (AONBs)**: An area of countryside designated by a government agency as having natural features of exceptional beauty and therefore given a protected status. In Scotland, these regions are defined as National Scenic Areas (NSA), but share the same designation as AONBs (Natural England, 2016a, Natural Resources Wales (2016), Scottish Government (2011)).

In addition, there are a number of Nature Designations which are designed to protect wildlife within the UK. The designations and data sources are as follows:

- **Sites of Specific Scientific Interest (SSSIs)**: these are the basic building block of site-based nature conservation legislation and most other legal nature/geological conservation designations in the United Kingdom are based upon them.
- **Special Protection Areas (SPAs)**: a designation under the European Union Directive on the Conservation of Wild Birds. Under the Directive, Member States of the European Union (EU) have a duty to safeguard the habitats of migratory birds and certain particularly threatened birds (JNCC, 2015).
- **National Nature Reserves (NNRs)**: established to protect some of our most important habitats, species and geology. Collected separately for England (Natural England, 2016b), Scotland (Heritage, 2017) and Wales (Natural Resources Wales, 2010b).
- **Special Areas of Conservation (SACs)**: a site designated under the Habitats Directive. UK wide data was collected (JNCC, 2015).
- **Ramsar sites**: also known as Natura 2000 sites, these are wetland areas designated of international importance under the Ramsar Convention (JNCC, 2015).

7.2.4 Topography

Elevation was collected from a Digital Elevation Model (DEM) of Europe at a 25m resolution (European Commission, 2015). This was used to calculate the gradient using the Fleming and Hoffer algorithm (Fleming & Hoffer, 1979) within the *raster* package in R.

7.2.5 Cumulative Density

It has been seen within planning documents that proximity to other turbines was frequently raised as an issue, with the cumulative impact of wind energy planning developments, and this review was reflected within literature (Eltham et al., 2008). Therefore, the location and year of the wind energy planning application was used to derive the nearest turbine at the time of planning.

7.2.6 Unavailable Datasets

There are often concerns surrounding the ecological impacts of wind energy on wildlife such as birds and bats. However, there was insufficient data concerning these issues to be integrated within the national analysis. Several maps have been produced by the RSPB for England and Wales but do not cover Scotland, and are limited in their scope and coverage (Bright et al., 2006; J. A. Brigth et al., 2009).

In a dissertation project based on the themes of this thesis, a review of planning applications within the UK was conducted to identify stated reasons for rejection (Dimitriou, 2017). 60 planning applications and appeals were reviewed in the study, and several reasons were identified in addition to those raised within the literature review in Chapter 4. These included shadow flicker, ice throw, and concerns of local hydrological conditions being damaged due to the concrete required for construction of the turbine foundations. However, there was difficulty in collecting datasets to represent these more complex issues, and such issues were only raised in 5 of the projects. The parameters were therefore excluded from further analysis.

7.2.7 Processing Data

As the geographic data was collected from a range of sources, it was required that projections and coordinate systems were standardised. The coordinate systems were checked and transformed as required to OSGB36. Each dataset was then clipped to the study extent of Great Britain to create a uniform dataset for the analysis.

7.3 Local Socio-demographic Data

The literature review highlighted a range of demographic parameters which have been linked with the acceptance rates of wind turbines. This section therefore explains the collection of Census and Political data and the processing of this to make it suitable for analysis.

7.3.1 Demographic Data

Demographic data was collected from the 2011 UK Census (Office for National Statistics, 2016), collecting information on 1) *Qualifications*; 2) *Age*; 3) *Home Ownership* and 4) *Social Grade*. Whilst deprivation was considered as a potential variable in the analysis, it is not recommended to use this variable for analysis between England, Scotland and Wales, as different techniques are used to calculate the deprivation index in each country (DCLG, 2016). The datasets were summarised into the following variables:

- **Qualifications**: percentage of the population with Qualifications greater than Level 4, which include Degrees, Higher Degrees and professional qualifications.
- **Age**: median and mean age.
- **Tenure**: percentage of the population that own their property.
- **Social Grade**: percentage of People Social Class A or Class B.[1].

To be able to use the census data within the geospatial analysis, the tabular data was merged with boundary data (SASPAC, 2011, UK Data Service (2017)). Demographic data is provided at the Lower Super Output Area (LSOA) for England & Wales and Data Zone (DZ) for Scotland. These boundary types are broadly similar in their scope, and are sized to represent areas with a population between 1000 and 3000 people (ONS, 2016).

As the LSOA and DZ regions are defined determined by population count, the area of these region size vary depending on the population density of the region. This results in smaller zones in cities when compared to those in rural regions. This is an important consideration for wind turbines, as such projects are typically located in rural sites, and therefore it is not possible to capture high levels of accuracy of local demographics within sparsely populated regions.

7.3.2 Local Political Data

Planning decisions for turbines are influenced by the Local Planning Authority, which are the local political bodies within the UK (HM Government, 2014). In total, there are 405 local authorities across England, Scotland and Wales. Local political data was collected for the Conservatives; Labour, Liberal Democrat and the Scottish National Party (SNP), which between them hold 95% of seats within Great Britain.

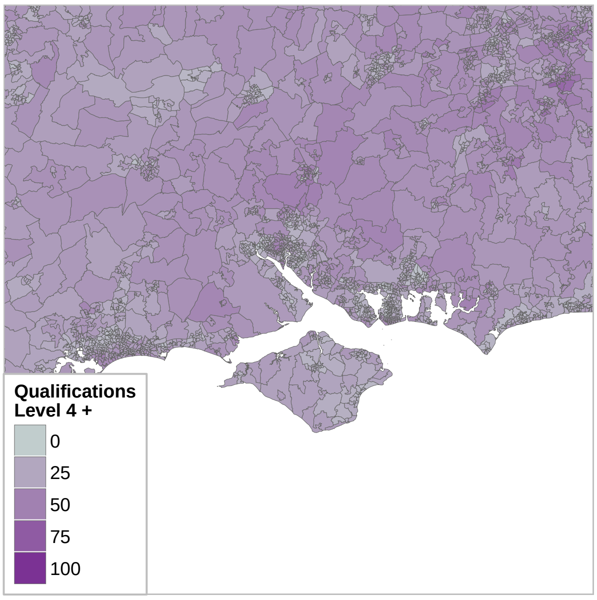
[1] A: High managerial, administrative or professional, B: Intermediate managerial, administrative or professional

Political data was collected for local councils from 1964 to 2015. To use this data, the data was reformatted into a single dataset for the period of collected wind turbine data, 1990 to 2017. Following this, the names of the boundaries were adjusted to allow for the dataset to be paired with the geospatial data, as explained in the following section.[2]

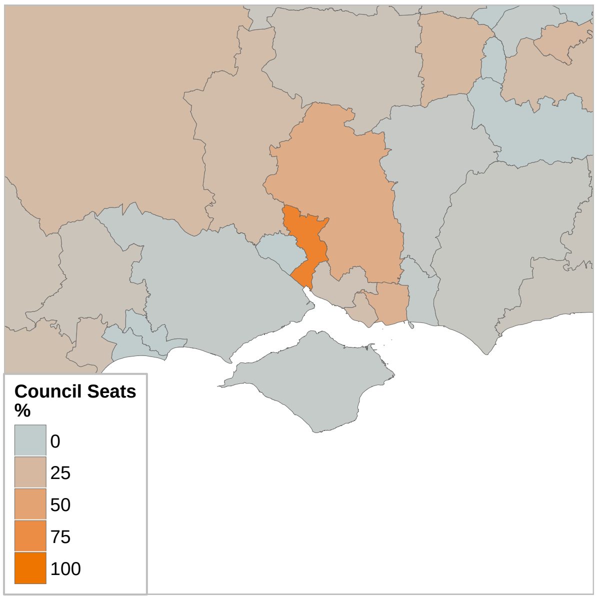
7.3.3 Results

The resulting dataset was joined to the census shapefile, with a total of 41258 separate regions for census data (which is collected at the Lower Super Output Area) and 380 political regions. Example variables are shown in Figure 7.1, highlighting the variation across the Solent region for levels of qualification and council share for Liberal Democrats, Labour and Conservatives. It can be seen that the zonal resolution between each dataset varies, with census data available at a much higher resolution.

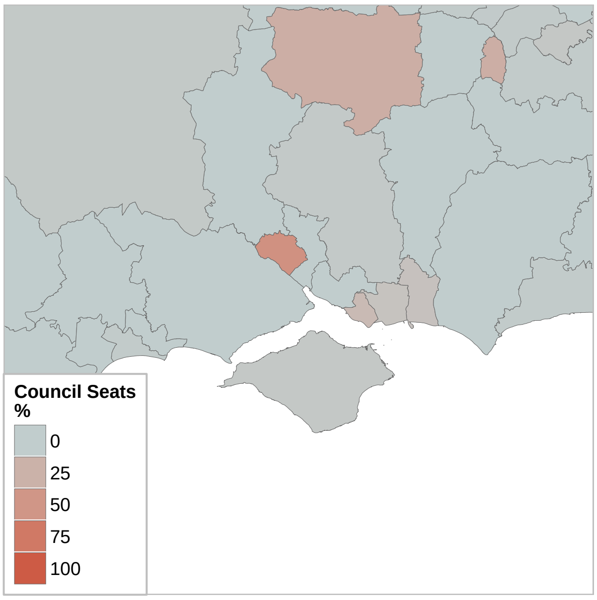
[2] A full description of the pairing process is provided here: `http://mikeyharper.uk/UK-Political-Data/`



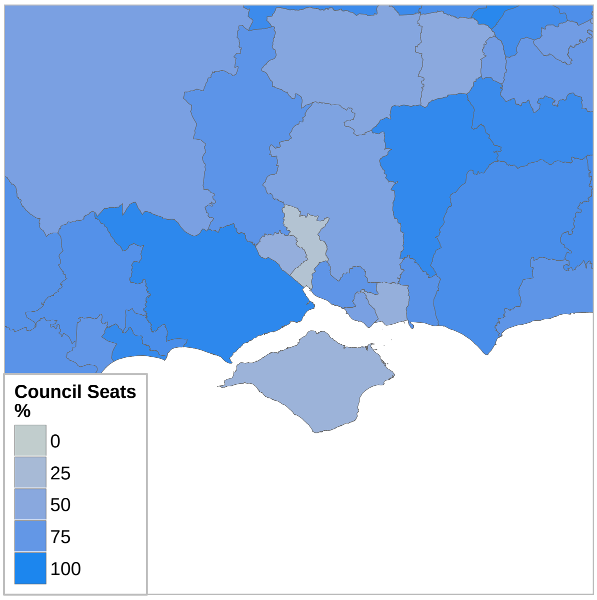
(a) Qualification Levels, percentage of people with qualifications level 4 or higher.



(b) Liberal Democrat Council Share, percentage of seats held within the local authority council, 2015.



(c) Labour, percentage of council seats, 2015.



(d) Conservative, percentage of council seats, 2015.

Figure 7.1: Census and Political Boundary Data for the Solent Region. Based on data from the 2011 Census (ONS,2016) and Results from the 2015 local council elections.

7.4 Extracting Data

Having prepared the geospatial, socio-demographic and wind energy project location data, combined datasets were prepared for the statistical analysis. As highlighted in Figure 7.2, two key datasets were produced for site locations and national characteristics. These two approaches are explained in detail within the following subsections.

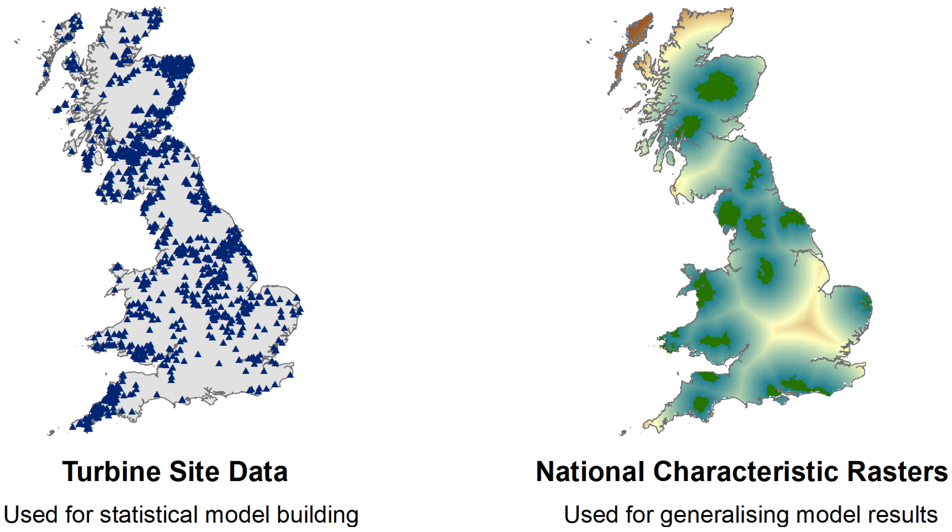


Figure 7.2: A summary of the two types of data extraction completed for the model parameters

7.4.1 Turbine Site Data

The aim of the analysis is to assess how proximity to certain features influences the acceptance rates of wind energy projects. Therefore, the data sources were aggregated for each wind energy project for each shapefiles and rasters using the following procedures:

- **Points, lines and polygons**: A spatial join using *rgeos* (Bivand & Rundel, 2017) was undertaken to determine the distance to the nearest feature for each project. A value of 0 is given if the project is within the feature.
- **Tabular**: sites were assigned the characteristics of the region they were within. 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 value of the raster was extracted from the location of the project.

The full list of site parameters is shown in Table 7.2. The table specifies the variable which each parameter represents.

Table 7.2: Table of parameters used within the statistical analysis.

ID	Category	Variable	Variable Value	Value Type	Unit
1	Turbine	Wind Turbine Planning Data	Planning Outcome	Categorical	Accept/Reject
2		Turbine Capacity	Megawatts/turbine	Continuous	MW
3		Number of Turbines		Continuous	
4		Year		Discrete	
5		Country		Categorical	
6	Resource	Wind Speed	Annualised Wind Speed	Continuous	m/s
7	Features	Airports	Distance to Feature	Continuous	km
8		Roads *	Distance to Feature	Continuous	km
9		Railways	Distance to Feature	Continuous	km
10		Urban Areas	Distance to Feature	Continuous	km
11		HV Powerlines **	Distance to Feature	Continuous	km
12	Landscape	Areas of Outstanding Natural Beauty	Distance to Feature	Continuous	km
13		National Parks	Distance to Feature	Continuous	km
14		Heritage Coast	Distance to Feature	Continuous	km
15	Nature	Special Protection Areas	Distance to Feature	Continuous	km
16		National Nature Reserve	Distance to Feature	Continuous	km
17		Sites of Special Scientific Interest	Distance to Feature	Continuous	km
18		Special Areas of Conservation	Distance to Feature	Continuous	km
19	Geographic	Elevation	Height above sea level	Integer	m
20		Slope	Gradient	Continuous	%
21	Census	Level of Qualification	Higher than L4 ***	Continuous	%
22		Age	Mean	Continuous	Years
23		Social Grade	Social Grade AB ****	Continuous	%
24		Tenure	Home Ownership	Continuous	%
25	Political	Conservatives	Percentage of Council	Continuous	%
26		Labour	Percentage of Council	Continuous	%
27		Liberal Democrat	Percentage of Council	Continuous	%
28	Cumulative	Nearest Turbine	Distance to Feature	Continuous	km
29		Nearest Turbine (Accepted)	Distance to Feature	Continuous	km
30		Nearest Turbine (Rejected)	Distance to Feature	Continuous	km

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

7.4.2 National Characteristic Rasters

For each layer used within the model, proximity rasters were produced. The rasters provide two key purposes for the analysis: firstly, they allow the characteristics of wind energy sites to be compared against the national average, as discussed in Section 8.3. Secondly, they are used to generalise the finding of the statistical analysis for use within the GIS-MCDA in Chapter 9.

The Euclidean distance is found for each of the geographical features in the model. This provides the distance for each cell in the raster to the nearest feature. A resolution of 250 metres was used within the model, as this is the typical minimum spacing that is required between modern turbines (Meyers & Meneveau, 2012).

7.5 Conclusion

It was highlighted in Sections 3.2 and 4.3 that there are a wide range of technical, environmental and social parameters which have been connected to wind energy developments and the acceptability of projects. This chapter therefore aimed to build upon this previous literature, and describe the datasets collected within the context of Great Britain, the study region for this thesis.

Datasets were collected from a wide range of sources. As a result, pre-processing was required to standardise the datasets and ensure they could be integrated within future analysis. These processes also included the geospatial projection of tabular data (political and census) by using respective boundary data.

Having collected and processed the dataset, two key functions were performed. Firstly, the parameters were aggregated at each wind energy site. As will be shown in Chapter 8, this aggregation will be used to determine whether any parameter is influential in the planning acceptance of wind energy projects. Secondly, generalised rasters were produced for each layer within the model, which will be used within Chapters 8 and 9 to generalise the outcomes of the statistical model across the whole study region.

Chapter Summary

- Datasets collected from a total of 30 data sources, including physical, environmental and social parameters.
- Preprocessing was conducted to ensure all layers were in a consistent format for analysis.
- Political and demographic data was merged with relevant boundary data to allow for geographical referencing of the datasets.
- Contextual data was summarised for each wind energy project within the REPD for use within the statistical modelling in Chapter 8.
- Generalised rasters were created for each model parameter to be used within the geospatial modelling in Chapters 8 and 9

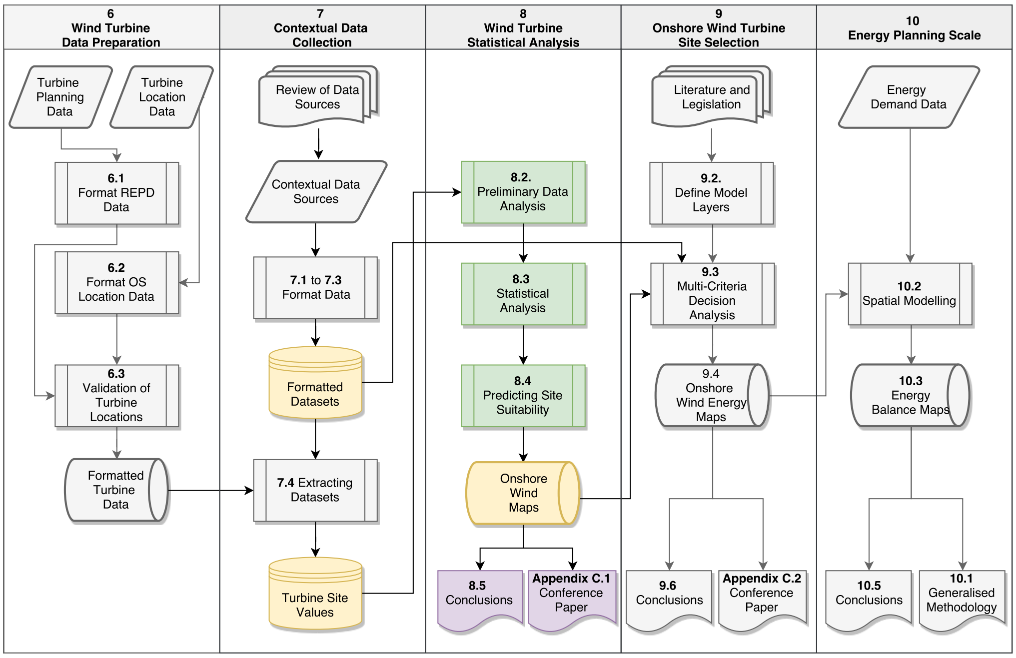
Part III

Analysis

- **Chapter 8**: statistical analysis is presented which assesses the influence of site parameters on planning acceptance rates.
- **Chapter 9** presents the results of the geospatial multi-criteria decision analysis for site selection of wind energy projects. This integrates economic, legislative and site acceptability to assess the suitability of sites for onshore wind development.
- **Chapter 10** explores the spatial implications of the optimal wind energy site placement suggested by Chapter 9. This combines data collected for energy demand and explores the potential for cities to meet their energy needs through onshore wind technologies.

Chapter 8

Wind Turbine Statistical Assessment



As highlighted within Section 4.2, there have been many GIS-MCDA models which have been developed within existing literature (Baban & Parry, 2001; Voivontas et al., 1998; Watson & Hudson, 2015). These utilise a range of geospatial parameters to identify suitable sites for wind energy development. However, there is a limited understanding of the input assumptions which are largely based on empirical evidence, and as a result concerns have been raised regarding the validity and accuracy of existing approaches (Langer et al., 2016). This chapter presents statistical analysis which investigates the relationship between planning decision outcomes and a range of explanatory variables included with literature, and has the following objectives:

- to validate the suitability of modelling data for statistical modelling.
- to make suitable adjustments to the model data to correct for potential issues within the modelling.
- to explain the iterative process used to conduct the statistical modelling.

- to identify the key influential parameters within the acceptance rate.
- to determine the overall fit of the statistical model for predicting acceptance rates.
- to generalise the findings of the model to predict the acceptance rates of wind energy projects.

Chapter Structure

As highlighted in Figure 8.1, the chapter is formed of three key parts:

1. **Preliminary Data Analysis** conducts a number of preliminary checks to the dataset. This aims to provide an insight into the dataset and to ensure that the datasets are suitable for the statistical analysis.
2. **Statistical Analysis** explains the statistical modelling used to assess the planning acceptance rates of wind energy planning applications. Four different modelling approaches were developed to determine a suitable model.
3. **Generalisation of Results:** utilises the results from the statistical analysis, and explains the process of generalising the model so that it can be used to predict the likelihood of acceptance of projects.

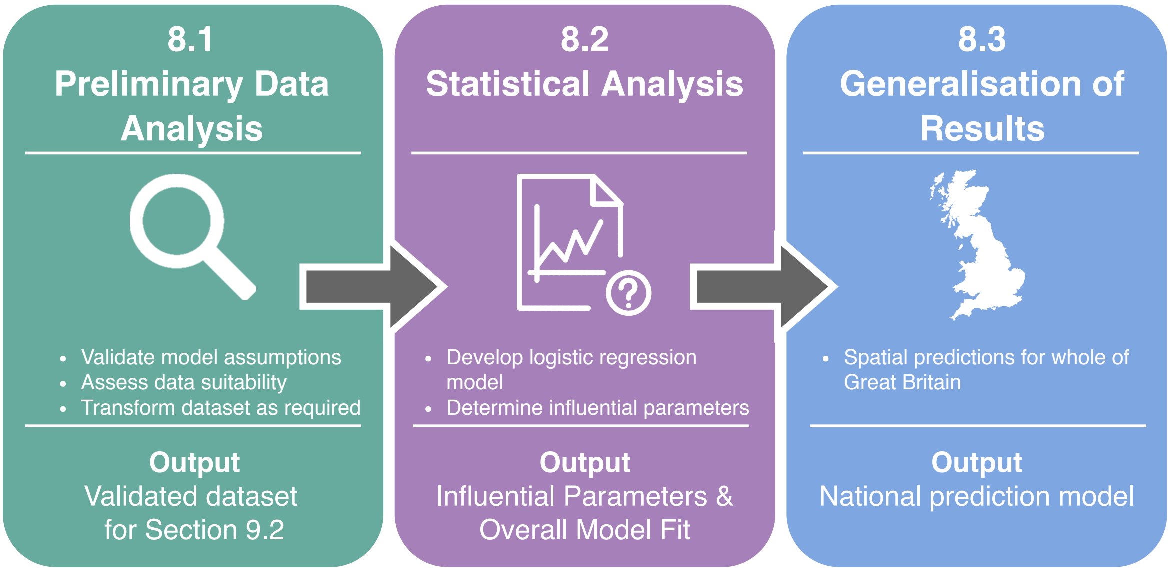


Figure 8.1: Stages of Statistical Analysis.

Following each section, a discussion concludes the key points. The chapter aims to highlight the development process which shaped the analysis, and explain the rationale for the decisions made within the modelling.

8.0.1 Statitical Analysis

The overall aim of the model is to predict the likelihood of a wind turbine project receiving planning approval. This statistical analysis is based on a logistic regression model, which can be used to assess binary relationships in categorical data. A brief primer of the theory and key concepts of logistic regression is included in Appendix A. In addition, Appendix B provides the full outputs of the statistical analysis.

8.1 Preliminary Data Analysis

It has been noted that statistical models are fundamentally influenced by the quality of the data used to build them (Harrell, 2001, p. 26). Failing to understand any limitations within the dataset can result in misspecified statistical models. It is therefore critical that checks are conducted to fully understand any potential issues within input parameters before modelling, and that any assumptions required for the statistical analysis are met. This section therefore presents the preliminary analysis conducted to understand the dataset.

8.1.1 Summary Statistics

Summary statistics provide a useful overview of the modelling data, and can provide an indication of issues which may warrant further exploration. Table 8.1 presents these statistics for the numeric variables within the model. It can be seen that the geospatial proximity to features used within the study vary significantly in their range. For example, the maximum distance a wind energy project is from *Urban Regions* is 7.7km while *Heritage Coast* has a range of 393.8km. Such a large difference in range can create difficulty in interpreting results, as a unit change of 1km has a much larger impact on the *Urban Region* parameter than *Heritage Coast*.

While previous studies have transformed the parameters to a standardized scale by using a z-score linear transformation (Rensburg et al., 2015), it was decided that they would be left unaltered within approach: such a 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 (Harrell, 2001, p. 123).

8.1.2 Missing Values

Logistic regression cannot directly deal with missing values within the dataset, and if an observation lacks any single parameter, the whole record will be removed from the data. This can result in a loss of data and potential impact on the modelling results, as a smaller sample size is used to build the model. It is therefore recommended that missing values are assessed, and where appropriate, imputed to create complete records (Harrell, 2001, Griffith (2003)).

It can be seen within the summary table that there are few cases of missing data across the total dataset (n =1691), with a total of 2.7% observations being incomplete. It was found that Slope, Elevation and Wind Speed missing data was a result of the rasterisation of the input dataset, with sites near the edge of land (rivers, coastline, lakes etc.) being occasionally lost within the dataset. Further missing data was seen within the political data, which resulted from boundary changes in 1995 which made it not possible to map, and the SNP party only exist within Scotland.

Table 8.1: Summary statistics of the parameters collected for onshore wind energy within the statistical analysis. These values represent the dataset before missing values were imputed

	mean	sd	median	min	max	skew	n
Turbine Capacity MW	1.9	1.0	2.0	0.0	10.0	0.2	1691
Capacity	18.9	31.2	10.0	1.0	652.0	8.1	1691
Year	2008.5	4.9	2009.0	1991.0	2017.0	-0.9	1691
Nearest Turbine (Operational)	13.7	27.2	6.7	0.0	561.2	8.6	1691
Nearest Turbine (Planned)	10.1	24.8	4.5	0.0	561.2	10.8	1691
Nearest Turbine (Rejected)	18.2	29.3	8.7	0.0	303.8	4.2	1691
Distance to Airports	25.9	23.3	20.3	0.0	174.6	2.9	1691
Distance to AONB	26.4	17.9	25.0	0.0	95.9	0.7	1691
Distance to A Roads	5.1	5.2	3.4	0.0	37.3	2.2	1691
Distance to B Roads	3.3	3.3	2.4	0.0	27.4	2.7	1691
Distance to Heritage Coast	107.9	83.4	98.3	0.0	393.8	1.1	1691
Distance to HV Powerlines	4.9	8.2	2.6	0.0	82.9	5.5	1691
Distance to Military Sites	22.2	18.8	17.4	0.8	137.2	2.5	1691
Distance to Minor Roads	1.0	1.1	0.7	0.0	7.8	2.2	1691
Distance to Motorways	55.6	64.5	30.8	0.0	323.0	1.8	1691
Distance to National Park	45.5	36.9	37.6	0.0	210.6	1.4	1691
Distance to NNR	18.3	13.8	15.1	0.1	98.0	2.0	1691
Distance to Powerlines	4.9	8.2	2.6	0.0	82.9	5.5	1691
Distance to Primary Roads	6.1	9.9	3.5	0.0	88.6	4.9	1691
Distance to Railways	9.4	14.2	5.0	0.0	121.6	4.0	1691
Distance to Ramsar	19.5	17.2	15.2	0.0	107.0	1.9	1691
Distance to SACS	7.9	7.2	6.0	0.0	46.6	1.8	1691
Distance to Natura 2000	12.1	10.7	9.1	0.0	69.6	1.6	1691
Distance to SSSI	3.0	2.3	2.5	0.0	13.3	1.2	1691
Distance to Large Urban Areas	6.5	6.0	4.9	0.0	61.2	2.5	1691
Distance to Urban Region	1.6	1.3	1.3	0.0	7.7	1.4	1691
Distance to Small Urban Areas	1.8	1.3	1.5	0.0	11.3	1.7	1691
Site Slope	3.1	3.1	2.3	0.0	21.4	2.1	1678
Elevation	179.9	144.9	149.0	0.0	684.0	0.7	1685
Wind Speed	7.4	1.1	7.0	4.0	12.0	0.4	1682
Mean Age	42.8	3.5	42.9	26.9	54.8	-0.4	1691
Qualifications, L4	27.6	8.4	28.0	5.0	56.0	0.0	1691
Social Grade AB	21.7	8.8	20.7	3.3	61.1	0.4	1691
Home Ownership	401.6	180.3	377.0	62.0	1195.0	0.6	1691
House Ownership	72.5	11.0	74.0	10.0	96.0	-1.1	1691
Political, Conservative Share	26.1	25.1	20.6	0.0	97.5	1.0	1666
Political, Labour Share	24.0	23.9	12.9	0.0	100.0	0.9	1666
Political, Liberal Democrat	15.1	14.7	11.2	0.0	70.6	1.1	1666
Political, Other	20.6	21.7	11.8	0.0	100.0	1.5	1666
Political, SNP Share	25.2	14.3	26.5	0.0	65.0	-0.1	937

[a] Political data represents the number of seats held within the local council, not the vote share. This explains why the range can vary between 0 and 100

Two techniques were used to impute missing datasets (Mandel J, 2015). Firstly, mean substitution was used to impute missing slope, elevation and political data. For the SNP data, any missing values which were in England and Scotland were imputed as 0.

8.1.3 Influential Outliers

Influential outliers are observations where values deviate from the expected range and produce extremely large residuals (Hosmer & Lemeshow, 2004). These can result in incorrect inferences from the statistical model, as the model may overfit to these extreme cases. It is therefore recommended that assessments are made before statistical modelling is conducted to identify potential cases which may need removal.

Figure 8.2a highlights the distribution of proximity variables, and provides a visual method to identify potential errors. The boxplots highlight that many parameters have outliers, which are largely caused by a narrow interquartile range resulting from the low standard deviations within the dataset. As the outliers are relatively evenly spread throughout the dataset, with few extreme values, they are of limited concern within the modelling.

The extreme values are in part caused by regional differences in landscape designation. For example, Heritage Coast designations are only present in England and Wales, resulting in projects in Scotland being consistently far away from these types of sites. There are a large number of projects which are more than 300km away from the nearest Heritage Coast designation.

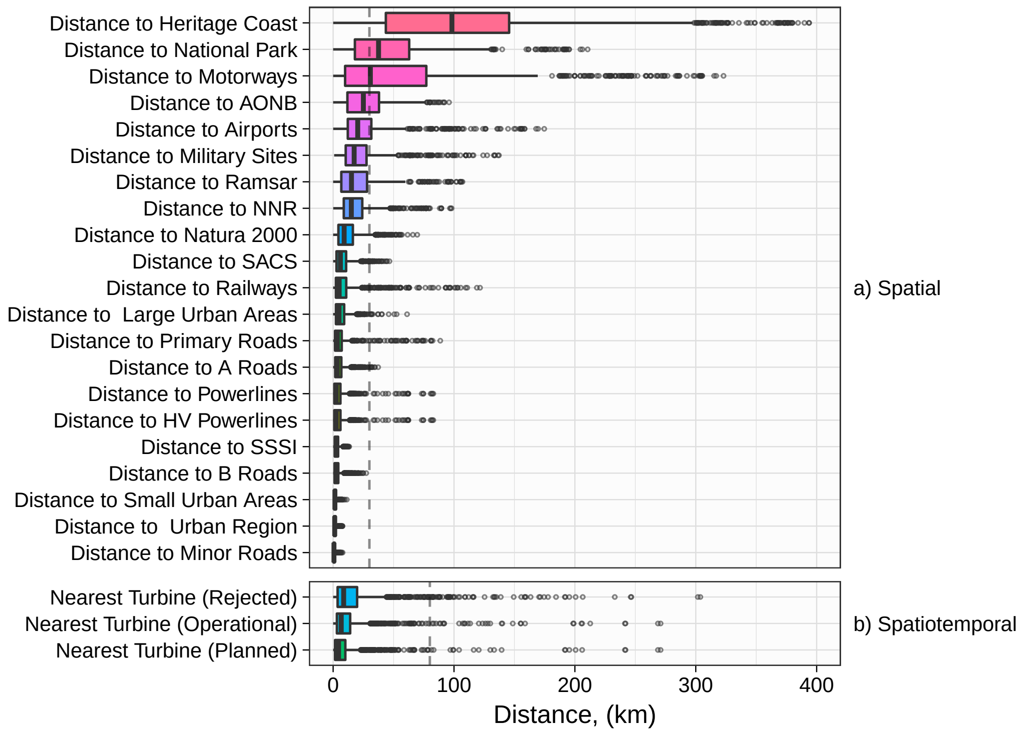


Figure 8.2: Boxplot for proximity variables which were derived from model parameters. A different censoring distance was applied to Spatial and Spatiotemporal datasets (30km and 80km respectively).

A second boxplot is shown in Figure 8.2b which highlights the "*Nearest Turbine*" parameter dataset. These are represented separately as their derivation used a different approach to the other geospatial proximity parameters, considering both the *location* and the *year* of the development. This has resulted in a small number of extreme outliers which represent sites which were the first to be developed within a region. Only 16 sites were further than 100km from other planned wind energy application sites.

8.1.4 Censoring Data

The boxplots in Figure **??** highlighted that there are many sites which are geographically distant from particular features. For example, the furthest site from a Heritage Coast designation is 394km. As would be expected, the planning decision[1] for this particular project made no reference to the Heritage Coast, as clearly a site would not be influenced by a landscape designation so far away. It was therefore important that adjustments were made to the dataset to reduce the impact of such sites on the statistical modelling.

Censoring was used to handle the large values within the model. Compared to truncation, whereby the data points are removed from the model, censoring retains the value but limits it a maximum value. Two separate censoring values were selected for the datasets:

1. For the spatial datasets, it was decided to censor the values to a maximum of 30km. This value was selected as it is the maximum distance at which wind turbines are typically deemed to have potentail visual impacts (Scottish Government, 2008).
2. For the spatiotemporal datasets (nearest turbines), literature suggests that regional scale perceptions to wind energy can be influenced by wind turbines, even if it is not visible from the other site (Eltham et al., 2008). A value of 80km was therefore selected, as this is the furthest that any site in the UK is now from a wind turbine.

Distance to Airports was the only exception for the censoring process, as there is generally a greater impact caused by wind turbines due to flight paths and radar (Civil Aviation Authority, 2016).

8.1.5 Collinearity

Collinearity between predictor variables can impact on the fit of models, resulting in inflated standard errors of regression coefficients and reducing the power of corresponding tests (Harrell, 2001, pg.64). As a result, checks are recommended to be made both before and after the model has been built. A correlation matrix is shown in Figure 8.3 which displays the pairwise Pearson product-moment correlation coefficient, and provides a means to visually inspect potential collinearity. The results indicate a number of key relationships:

[1]See `https://goo.gl/mUA7QL` for the planning decision documentation

- **Number of Turbines** and **Capacity** ($R^2 = 0.87$): unsurprisingly, this suggests that wind farms with more turbines will have more overall capacity.
- **Qualifications** and **Social Grade** ($R^2 = 0.88$): this suggests that those who attain higher professional positions would typically have higher levels of qualifications.
- **A number of proximity features**: many features (powerlines, roads, railways, military sites) are indicated to have a high level of correlation.
- **Grouping of linked parameters**: A number of parameters were split or derived from the same datasets which would be expected to be highly correlated. These include 1) *Small*, *Large* and *All Urban Areas* and 2) *Nearest Turbines All*, *Nearest Turbine Planned*, *Nearest Turbine Rejected*.

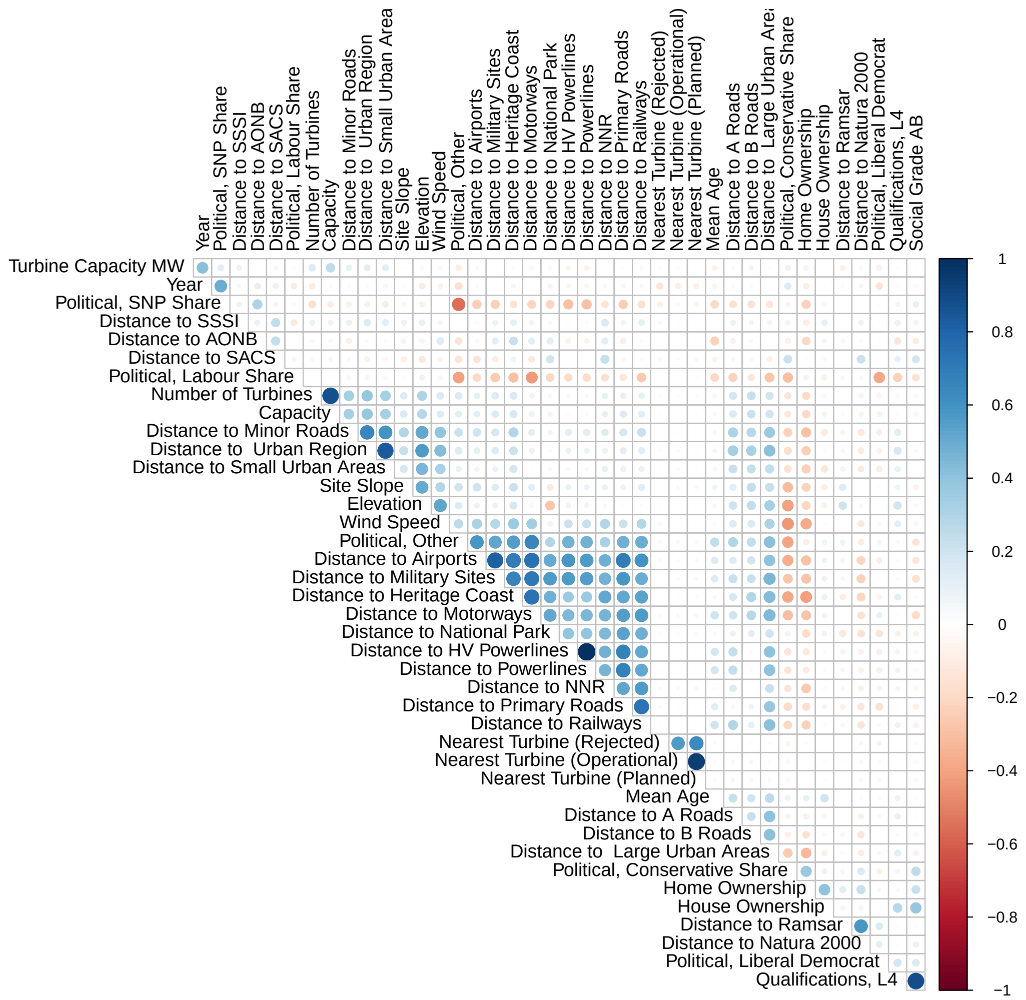


Figure 8.3: Bivariate correlation matrix for predictor variables within the analysis.

Whilst these correlations provide an important insight into the dataset, it is not recommended that such observations are used as the sole justification for removing parameters from the model. However, these results raise concerns which should be explored further, and therefore additional assessments of multicollinearity were made within the statistical analysis, as presented in Section 8.2.

8.1.6 Linearity of Logit

As briefly discussed within the influential outliers section, logistic regression assumes linearity between the predictor variable and the logit (Harrell, 2001). Assessments were therefore conducted to assess this assumption, with smoothed scatter plots shown in Figure 8.4, whereby each point represents an aggregated percentile. Linearity can be assessed by the shape of the fitted curve, and the magnitude of the potential influence is indicated by the gradient of this fit. The following general observations were made:

- **Linearity of relationships**: most proximity features appear to have a linear relationship (AONBs, National Parks, Military, Natura 2000 sites).
- **Non-linearity**: Notable examples include Liberal Democrat voter share, and distance to urban areas.
- **Social Grade, Mean Age and Qualifications**: all three of these variables appear to negatively influence the planning acceptance rates. Combined with the high levels of correlation, these again may suggest multi-collinearity between the variables.
- **Overfitting of curves**: although efforts were made to remove influential outliers, some graph appear influenced by non-linear relationships (e.g. Heritage Coast, Small Urban Areas, Primary Roads).

Whilst transformations can be used to correct non-linear relationships, it is recommended that these are only made with a valid hypothesis: attempting to make transformations for the purpose of improving model fit can introduce type I errors and also limit the interpretability of the resulting model (Harrell, 2001). It was observed within existing GIS wind turbine studies that linear relationships are primarily used. As a result, it was decided that no transformations were to be made to the dataset.

Again, while these results can help indicate potential issues, it is not recommended that parameters are removed prior to the analysis based on these results. There is the potential that the interaction with other variables within the model may alter these relationships, and therefore further linearity checks are conducted within the diagnostics of the statistical modelling.

8.1.7 Summary of Preliminary Data Checks

This section has presented the preliminary data analysis conducted on the model data. Several potential issues were raised, with alterations being made to the dataset to ensure the suitability of the model data. In addition, concerns were raised surrounding potential collinearity and the linearity of the logit; however no parameters have been excluded from the analysis on this basis. Further checks will build upon these findings within the following section.

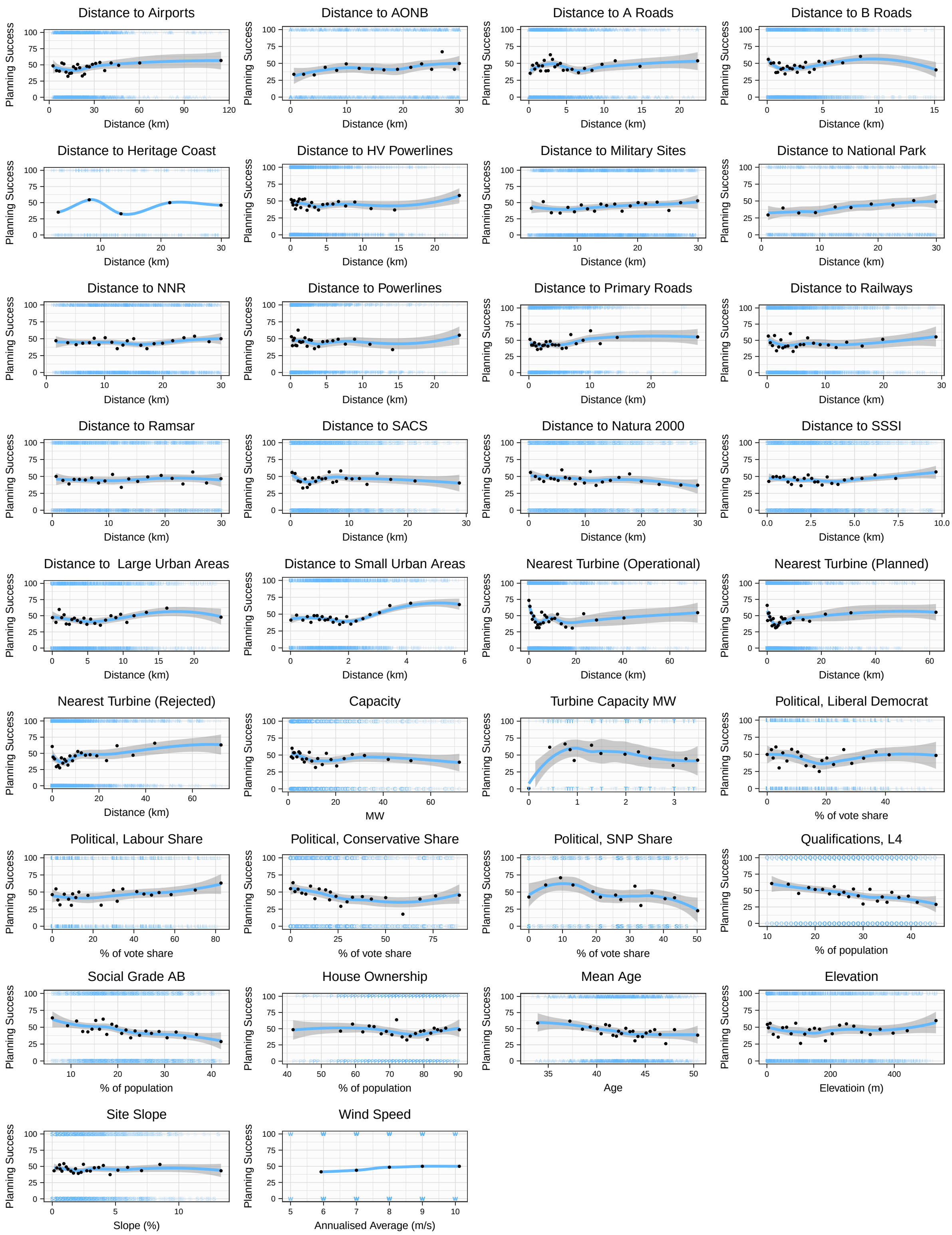


Figure 8.4: Scatter plots showing proportion of sites receiving planning against each predictor variable. The graph uses the censored datasets as described within this chapter. Individual observations are shown in the rug plots which highlight the marginal distributions.

8.2 Statistical Analysis of Wind Energy Acceptance Rates

Section 8.1 presented the measures taken to ensure the suitability of the model data for further analysis. This section presents the iterative development of the models used, and covers the four following methods:

1. **Hierarchical Model**: this section presents the initial regression model formed by sequentially adding groups of parameters to the model.
2. **Parsimonious Model**: optimisation was run to reduce the number of variables included within the model.
3. **Subset Models**: the model was split into temporal and regional subsets to explore the variance in local parameters within the global model.
4. **Geographically Weighted Regression Model**: building upon the subset models, weighting is applied to the regression modelling to explore for localised impacts.

It should be noted that only a short discussion is provided following each model, which focuses on explaining the rationale of the refinement process. The overall discussion is included within the conclusions in Section 8.2.5, which reviews the overall model results and discusses influential parameters identified.

Model Approach

Logistic regression analysis was used to assess the influences of a range of predictor variables on the planning acceptance of wind energy projects. This is based on the wind energy planning data collected within the REPD and processed within Chapter 6, whereby sites are classed as either rejected (0) or accepted (1). The logistic regression formula is as follows:

$$\text{Probability of Outcome}(Y_i) = \frac{e^{\beta_1 X_1 + \beta_2 X_2 + b_3 X_3 + \ldots + b_j X_j}}{1 + e^{\beta_1 X_1 + \beta_2 X_2 + b_3 X_3 + \ldots + b_j X_j}} \tag{8.1}$$

where Y_i represents the estimated probability of being in one binary outcome category i versus the other, and $e^{\beta_1 X_1 + \beta_2 X_2 + b_3 X_3 + \ldots + b_j X_j}$ represents the linear regression equation for independent variables expressed in the logit scale, instead of the original linear format.

For each model developed within the analysis, the suitability was assessed and diagnostics conducted, including the Hosmer-Lemeshow goodness of fit test (Hosmer & Lemeshow, 2004). Model parameters were assessed for linearity of the logit, and collinearity identified using the Variance Inflation Factor (VIF). Any parameters which violated the assumptions of logistic regression modelling were removed from the analysis to prevent distortion of the model.

To further validate the model fit, the model's accuracy was assessed using K-fold internal validation. This approach splits the data into a K number of subgroups, with $(K-1)$ number of groups being used to "train" the model, while the remaining group is used to "test" the model. This process is repeated for each of the subgroups, allowing for a resilient test which can be used to validate the model without excessively reducing the building sample size (Hosmer & Lemeshow, 2004).

8.2.1 Hierarchical Logistic Regression Model

It was shown in Section 4.2 that existing literature placed an emphasis on physical characteristics when assessing the suitability of a site for wind energy development. However, qualitative studies have indicated that socio-demographic parameters are important within the acceptability of wind energy (Langer et al., 2016), although to the authors knowledge, no GIS models have integrated these within their analysis directly.

A hierarchical approach was therefore applied to build the first model, whereby variables were added sequentially to the model. This is suitable for where a hypothesis based on a predetermined order of importance, as it allows for the relative impact of each group of parameters to be assessed (Harrell, 2001). The following hierarchy was therefore developed for the analysis:

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 the planning application was made.
4. **Proximity to Features**: inclusion of proximity to geographic features, Landscape and Nature Designations
5. **Social and Census Data**: Demographic data for the area of the wind energy project, including *Mean Age* and *Level of Qualifications*.
6. **Political Data**: the political composition of the local authority composition at the time of the planning application.
7. **Spatial Proximity to Other Turbines**: considers the proximity to the nearest wind energy project in order to assess cumulative impacts.

Results

A summary of the stages of the hierarchical model is shown in Table 8.2. It can be seen that there is a marginal improvement of the Nagelkirke R^2 values across the results, and that the predictive accuracy marginally improves as more parameters are included within the model. For the Hosmer-Lemeshow test, the final model reports a p-value of 0.032, which indicates that the null hypothesis holds that the model fits the data. The results for the parameters included within the complete model (Model 7) are shown in Table 8.3, which indicates the statistically significant parameters. The odds ratios (OR) are presented, with an OR $= 1$ indicating the parameter does not affect odds of the planning outcome, an OR > 1 indicating the parameters positively influences planning acceptance, and an OR < 1 represents a negative parameter influence.

Table 8.2: A summary of the hierarchical logistic regression models.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Observations	1685	1685	1685	1685	1685	1685	1685
Parameters	3	5	6	22	25	28	31
Deviance	2303.2	2297.61	2211.43	2139.69	2108.01	2105.38	2069.23
R.n	0.016	0.020	0.086	0.138	0.160	0.162	0.187
Chi Square	20	25	112	183	215	218	254
Degrees of Freedom	2	4	5	21	24	27	30
p	5e-05	4e-05	0.000	0.000	0.000	0.000	0.000
Residual Deviance	1682	1680	1679	1663	1660	1657	1654
AIC	2309	2308	2223	2184	2158	2161	2131
Accuracy [a]	55%	56%	62%	64%	64%	64%	66%

[a] Accuracy assessed by internal validation using a random sample of 5% with 200 iterations.

Model Comments

The results presented in Table 8.2 indicate that the model has a relatively poor overall fit, and that with the full set of parameters included, the Nagelkirke R^2 value is only 0.187. To address these concerns, more advanced logistic regression modelling techniques were explored to improve the model fit, as explained in the following sections.

8.2.2 Parsimonious Model

The hierarchical approach considered the full list of model variables, resulting in a relatively complex model. However, it can be seen that a large proportion of these variables have a low estimate value and statistical significance, and their inclusion provides minimal improvement to the model fit. Before advanced optimisation techniques were considered, the number of model parameters was reduced to create a parsimonious model.[2]

The backward elimination technique was used to develop parsimonious models. In this approach, all candidate variables are included within the model, and the deletion of each variable is tested using a chosen model fit criterion, deleting the variable (if any) whose parameter results in the least deterioration in the model fit. This process is repeated until no further variables can be deleted without a statistically significant loss of fit (Hosmer & Lemeshow, 2004).

Alternative elimination techniques were considered within the analysis, as there are concerns about the accuracy of backward elimination model in removing parameters. Interaction between parameters may lead to a parameter scoring poorly in the presence of other variables while being significant in a different sub-model (Harrell, 2001). An *"all-subset"* approach was therefore explored, which considers all potential parameter combinations and selects the one with the best

[2] A parsimonious model is a model that accomplishes a desired level of explanation or prediction with as few predictor variables as possible

Table 8.3: Parameter results for the complete hierarchical logistic regression model (Model 7)

Variable	Estimate	Std. Error	z value	Pr	Sig.	Odds Ratio	OR 2.5% CI	OR 97.5% CI
Number of Turbines	0.001	0.006	0.239	0.811		1.001	0.991	1.013
Turbine Capacity MW	0.346	0.067	5.184	0.000	***	1.413	1.241	1.612
Wind Speed	-0.090	0.063	-1.429	0.153		0.914	0.809	1.034
Distance to HV Powerlines	0.011	0.008	1.402	0.161		1.011	0.996	1.028
Year	-0.116	0.014	-8.394	0.000	***	0.890	0.866	0.915
	0.008	0.008	1.009	0.313		1.008	0.992	1.025
Distance to A Roads	0.000	0.012	0.032	0.974		1.000	0.976	1.025
Distance to B Roads	-0.022	0.019	-1.148	0.251		0.979	0.943	1.015
Distance to Minor Roads	0.060	0.070	0.857	0.391		1.062	0.926	1.219
Distance to Motorways	-0.002	0.007	-0.282	0.778		0.998	0.984	1.012
Distance to Railways	0.015	0.009	1.659	0.097	.	1.015	0.997	1.033
Distance to Urban Region	0.143	0.064	2.228	0.026	*	1.154	1.018	1.309
Distance to AONB	0.017	0.006	2.748	0.006	**	1.017	1.005	1.030
Distance to National Park	0.029	0.007	4.249	0.000	***	1.030	1.016	1.044
Distance to Heritage Coast	-0.009	0.009	-1.011	0.312		0.991	0.973	1.009
Distance to NNR	-0.002	0.007	-0.348	0.728		0.998	0.984	1.011
Distance to Ramsar	0.012	0.007	1.824	0.068	.	1.012	0.999	1.026
Distance to SACS	0.001	0.010	0.105	0.916		1.001	0.982	1.020
Distance to Natura 2000	-0.018	0.008	-2.171	0.030	*	0.982	0.967	0.998
Distance to SSSI	0.031	0.025	1.235	0.217		1.032	0.982	1.084
Distance to Military Sites	0.001	0.008	0.150	0.881		1.001	0.986	1.017
Qualifications, L4	-0.031	0.007	-4.428	0.000	***	0.969	0.956	0.983
Mean Age	-0.041	0.017	-2.375	0.018	*	0.960	0.927	0.993
Home Ownership	0.000	0.000	0.480	0.631		1.000	0.999	1.001
Political, Conservative Share	-0.003	0.003	-0.775	0.439		0.997	0.991	1.004
Political, Labour Share	0.003	0.004	0.687	0.492		1.003	0.995	1.010
Political, Liberal Democrat	0.001	0.005	0.190	0.849		1.001	0.991	1.011
Nearest Turbine (Operational)	-0.015	0.004	-3.765	0.000	***	0.985	0.977	0.993
Nearest Turbine (Rejected)	0.019	0.003	5.738	0.000	***	1.019	1.013	1.026
Distance to Large Urban Areas	-0.006	0.013	-0.464	0.643		0.994	0.969	1.020

[a] Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

fitting. However, it was found to offer no improvement, whilst being computationally intensive to run. The backward elimination approach was therefore deemed suitable for the analysis.

Results

The results for the reduced model are presented in Table 8.4, and the odds ratios are shown graphically in Figure 8.5. The total number of parameters in the parsimonious model was reduced from 30 to 13. This has led to a marginal improvement in the AIC from 2131 to 2107. However, this has marginally reduced the model fit, with the Nagelkirke R^2 value reducing from 0.187 to 0.180. Finally, the predictive accuracy of the model was determined as 66%.

Table 8.4: Results from the parsimonious logistic regression model

Variable	Estimate	Std. Error	z value	Pr	Sig.	Odds Ratio	OR 2.5% CI	OR 97.5% CI
Turbine Capacity MW	0.349	0.064	5.431	0.000	***	1.418	1.251	1.610
Year	-0.117	0.013	-8.949	0.000	***	0.889	0.867	0.912
Distance to Railways	0.018	0.008	2.432	0.015	*	1.018	1.004	1.034
Distance to Urban Region	0.130	0.045	2.908	0.004	**	1.139	1.044	1.244
Distance to AONB	0.015	0.005	2.672	0.008	**	1.015	1.004	1.026
Distance to National Park	0.026	0.006	4.255	0.000	***	1.026	1.014	1.039
Distance to Ramsar	0.014	0.006	2.325	0.020	*	1.015	1.002	1.027
Distance to Natura 2000	-0.017	0.007	-2.230	0.026	*	0.984	0.969	0.998
Qualifications, L4	-0.032	0.007	-4.770	0.000	***	0.968	0.956	0.981
Mean Age	-0.042	0.016	-2.567	0.010	**	0.959	0.929	0.990
Political, Labour Share	0.004	0.002	1.434	0.152		1.004	0.999	1.008
Nearest Turbine (Operational)	-0.015	0.004	-3.732	0.000	***	0.985	0.977	0.993
Nearest Turbine (Rejected)	0.019	0.003	5.783	0.000	***	1.019	1.013	1.026

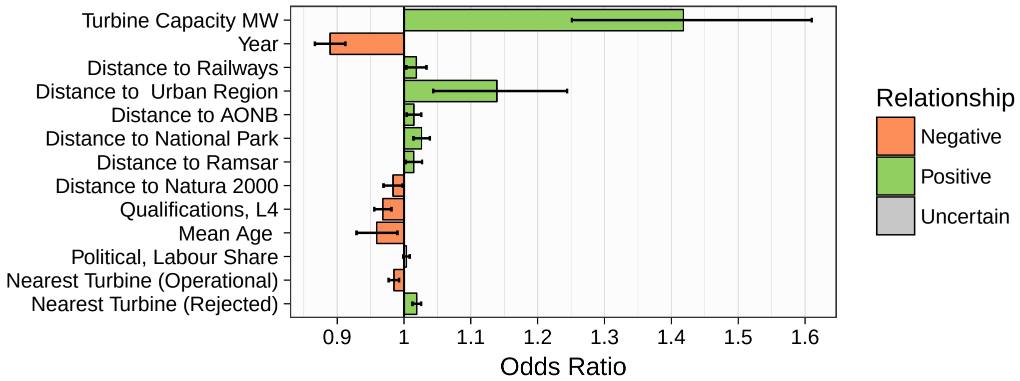


Figure 8.5: Logistic odds plot for the parsimonious model. Variables shown in either green or red are statistically significant positive or negative at 0.95 confidence interval.

Model Comments

The complexity of the model has been greatly reduced, with non-significant parameters being removed from the model. Whilst such a model does not improve the overall fit, the reduced numbers of parameters makes it easier to refine the model further, as explained in the following subsections.

8.2.3 Split Data Model

It was hypothesised that the parameters influencing the planning acceptance of wind energy may vary between countries within Great Britain. England, Scotland and Wales have varying demographics and population densities[3] as well as differing institutional support from national governments, with Scotland placing a greater emphasis on the development of onshore wind (Smith, 2016; Spath & Rohracher, 2012). It can also be seen that existing planning acceptance rates are lower in England (41%) than in Scotland (49%) and Wales (48%) (DECC, 2016c).

[3]The population density as of 2013 was England: 413/km^2, Scotland: 68/km^2, Wales: 149/km^2 (ONS, 2013).

However, the global model presented in Section 8.2.1 was not able to account for any regional variation in relationships.

Where significant variation is expected within subgroups, split data models are recommended, whereby the dataset is segmented into groups based on model variables, and regression models fitted to each subgroup (Stoltzfus, 2011). 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. A split data approach was therefore developed using the Country variable, creating three separate models for England, Scotland and Wales respectively.

It was shown in Section 8.2.2 that a parsimonious parameter list was developed, which found the most significant variables for the *global* model. However, it was also considered that there may be differing influential parameters between each *local* model. Therefore, two approaches used to select the parameters for the models:

1. **Global Parameter model**: each sub-model used the parsimonious model parameters (n = 13) as developed in Section 8.2.2.
2. **Optimised Parameter model**: The full list of parameters was provided for each model (n = 31). A backward step optimisation was used to eliminate non-influential parameters, similar to the approach used in 8.2.2.

Results

The results of the models are summarised in Table 8.5, which compares the two sets of split data models compared against the results of the global parsimonious model developed in Section 8.2.2. There has been a general increase in the fit of the models represented by the Nagelkirke R^2 values. For the Optimised parameter models, it can be seen that the number of parameters within each model varies between 13 and 16, as derived from the backward elimination process.

As the split models have been built using different datasets, there is greater difficulty in directly comparing the diagnostics to assess the model fit. Deviance, chi-sqared values, and residual deviance are all dependent on the size of the datasets. Therefore, the models were compared using the sum of the deviance of the split models, with values of 2041 and 1997 for the *Global* and *Optimised* models respectively. The influence of each parameter within the model are represented in the odds plots shown in Figures 8.6. It can be seen that there is variation of the odds ratios between countries, although the splitting of data has resulted in a larger margin of error. These regional differences are expanded upon within the discussion of this section.

Table 8.5: Comparison of subset Logistic Regression Models.

		Global Parameter			Optimised Parameters		
	Global	England	Scotland	Wales	England	Scotland	Wales
Observations	1685	728	796	161	728	796	161
Parameters	14	14	14	14	13	16	13
Deviance	2079.34	884.02	957.03	199.97	872.17	947.43	177.84
R.n	0.180	0.180	0.223	0.178	0.199	0.237	0.326
Chi Square	244	105	146	23	117	156	45
Degrees of Freedom	13	13	13	13	12	15	12
p	0.000	0.000	0.000	0.04092	0.000	0.000	1e-05
Residual Deviance	1671	714	782	147	715	780	148
Accuracy	66%	66%	67%	56%	67%	68%	63%

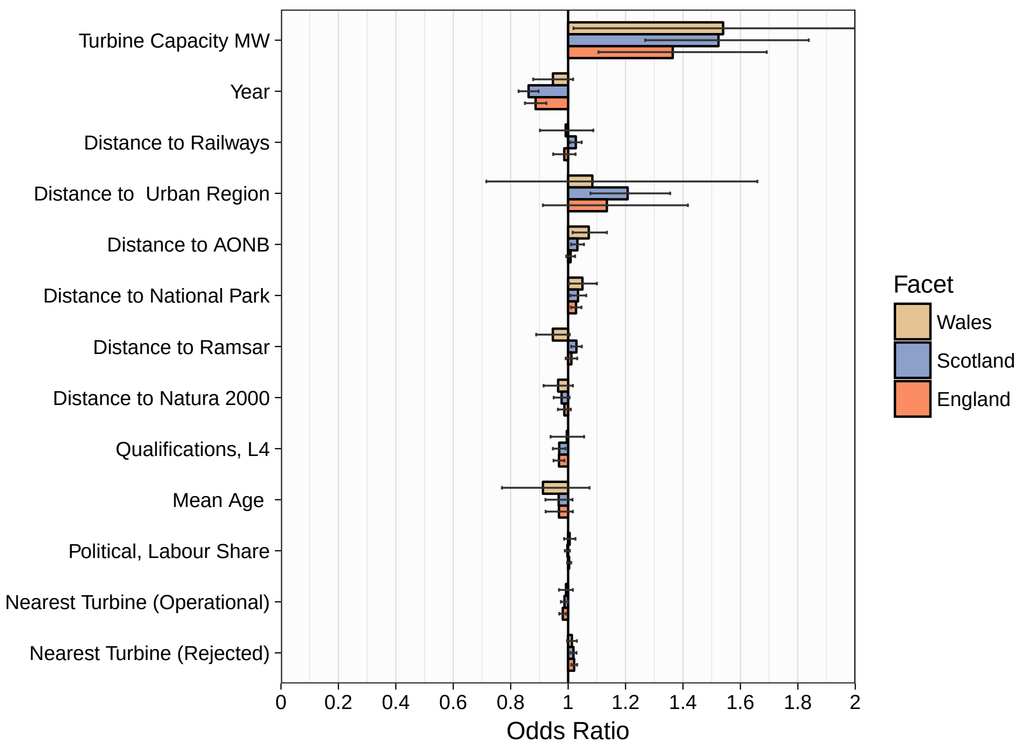


Figure 8.6: Odds plot for Multilevel regression models split by country in the UK.

There is evidence of over-fitting which has resulted from splitting the data into subsets. It is recommended that the number of parameters p in a model should not be less than $m/10$ where m is the *limiting sample size* min(n_1, n_2) (Harrell, 2001). The Wales model has limiting sample size of 78, which therefore should mean that no more than 7 should be used within the model. This over-fitting can is shown by the fact that despite a high Nagelkirke R^2 value (0.326) there is a low predictive accuracy (56%), indicating observed values do not agree with the predicted values.

8.2.4 Geographically Weighted Regression

Standard global modelling techniques cannot be used to detect local variations of the predictor variable. More specifically, the same stimulus provokes the same response in all parts of the study region. It was shown in the previous section that split data models were used to explore differences between subgroups in the model, however these could only capture variation for a predetermined spatial category (i.e. Country). However, there is evidence within the literature that the acceptability of wind turbines varies at a sub-national level (Horst & Toke, 2010). More advanced techniques were therefore explored to capture these regional variations.

To assess the suitability of the global model, the model residuals were mapped as shown in Figure 8.7. In a well-specified model, it would be expected to see that residuals varied randomly within the model, with no spatial correlation. However, there are clusters of high and low residuals, indicating that the model is under and over-predicting in certain regions. The Moran-I test was further used to assess the autocorrelation, and it was found that there was spatial clustering within the model ($p = 0.0002$) (Bivand, 2017). Such autocorrelation invalidates the assumption that residual values are independent of each other (Hosmer & Lemeshow, 2004), and therefore measures were taken to reduce these issues.

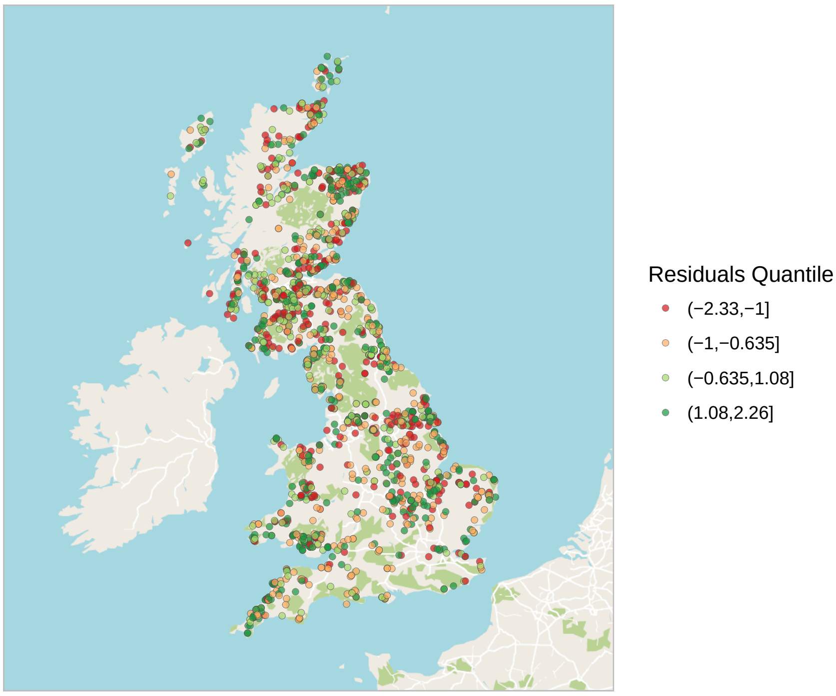


Figure 8.7: Mapped Residuals for the parsimonious logistic regression model.

To address the concerns of spatial nonstationarity[4] within the data, Geographic Weighted Regression (GWR) was used to account for the spatial location of points within the model (Brunsdon et al., 1996). This technique builds upon traditional regression modelling, and instead of fitting a single, global regression model, local regression coefficients are fitted to explore

[4] spatial nonstationarity is defined as a condition in which a simple "global" model cannot explain the relationships between some sets of variables (Brunsdon et al., 1996).

geographic differences in estimates across the study region. These local coefficients are obtained at each location in the model, with a regression model applied, whereby sites closer to the location have a greater influence than those further away.[5]

The relationship between the proximity of neighbouring site and the influence which they have on the model is specified by a gaussian kernel function, which requires a bandwidth to be specified. This can be either a fixed width or adaptive, whereby the bandwidth varies for each model to include a prespecified proportion of the observations, as demonstrated in Figure 8.8. As there is varying spatial density of wind energy projects within Great Britain, an adaptive width bandwidth was selected. This ensures that there are sufficient observations to produce a robust model, even in locations where there are few existing observations (Kasner et al., 2013).

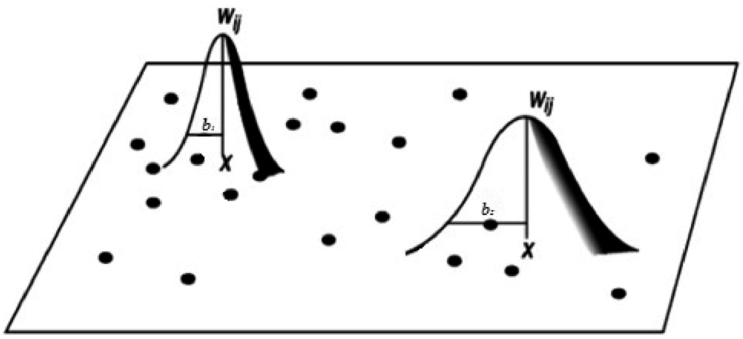


Figure 8.8: Spatial weighting functions with adaptive Bandwidth. Adapted from Fothering et al. (2002).

In order to determine the bandwidth size for the model, an optimisation is used whereby the bandwidth selection minimises the overall AIC of the model. For the parsimonious model parameters determined within section 8.2.2, an optimum adaptive bandwidth of 0.41 was calculated. This value represents the fraction of sites to be used, which equates to 690 observations per locally weighted model.

Results

The summary results are presented within this chapter while the full statistics are shown in Appendix B8. For the GWR model, the corrected Akaike Information Criteria (AICc) is 1198, in comparison with 2107 from the parsimonious regression model developed previously. The predictive accuracy of the model was estimated as 69%.

The Moran-I test was used to reassess the presence of spatial autocorrelation within the model. There has been a reduction in statistical significance ($z = 2.42$, $p = 0.01$). However, there remains a high level of autocorrelation within the model residuals, suggesting there may be further unexplained clustering within the dataset.

[5]For a brief primer on geographically weighted regression, the author recommends Kasner et al. (2013).

The local variation of parameters influence is shown in Figure 8.9, which maps the β estimates for each model parameter. It can be seen that the global estimate appears suitable for a number of parameters, although there is local variation seen within the model. These will be explored further within the discussion.

8.2.5 Discussion

This section has presented the development of the statistical analysis used to assess acceptance rates of wind energy. This discussion aims to summarise the key findings within the model.

Overall Model Reflection

The development of the hierarchical model was used to help assess the suitability of existing GIS studies. Models 1 and 2 from the initial hierarchical regression models indicate that the physical and economic characteristics are not influential in the acceptance rates of wind energy. This can be seen from both the low Nagelkirke R^2 values of 0.187, along with the high levels of residuals within the models. The largest improvement was found with the inclusion of the temporal data in Model 3, although the political and demographic data also provided a marginal improvement in model fit.

The parsimonious model highlighted several key parameters, as shown in Figure 8.5. Firstly, 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 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 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.

Significant Parameters

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 (Haggett & Toke, 2006; Jones & Richard Eiser, 2010) and rejecting (Devine-Wright, 2005a; Populus, 2005; Rensburg et al., 2015) the NIMBY argument. However this study provides quantitative evidence to suggest that that sites closer to urban areas have a lower chance of acceptance.

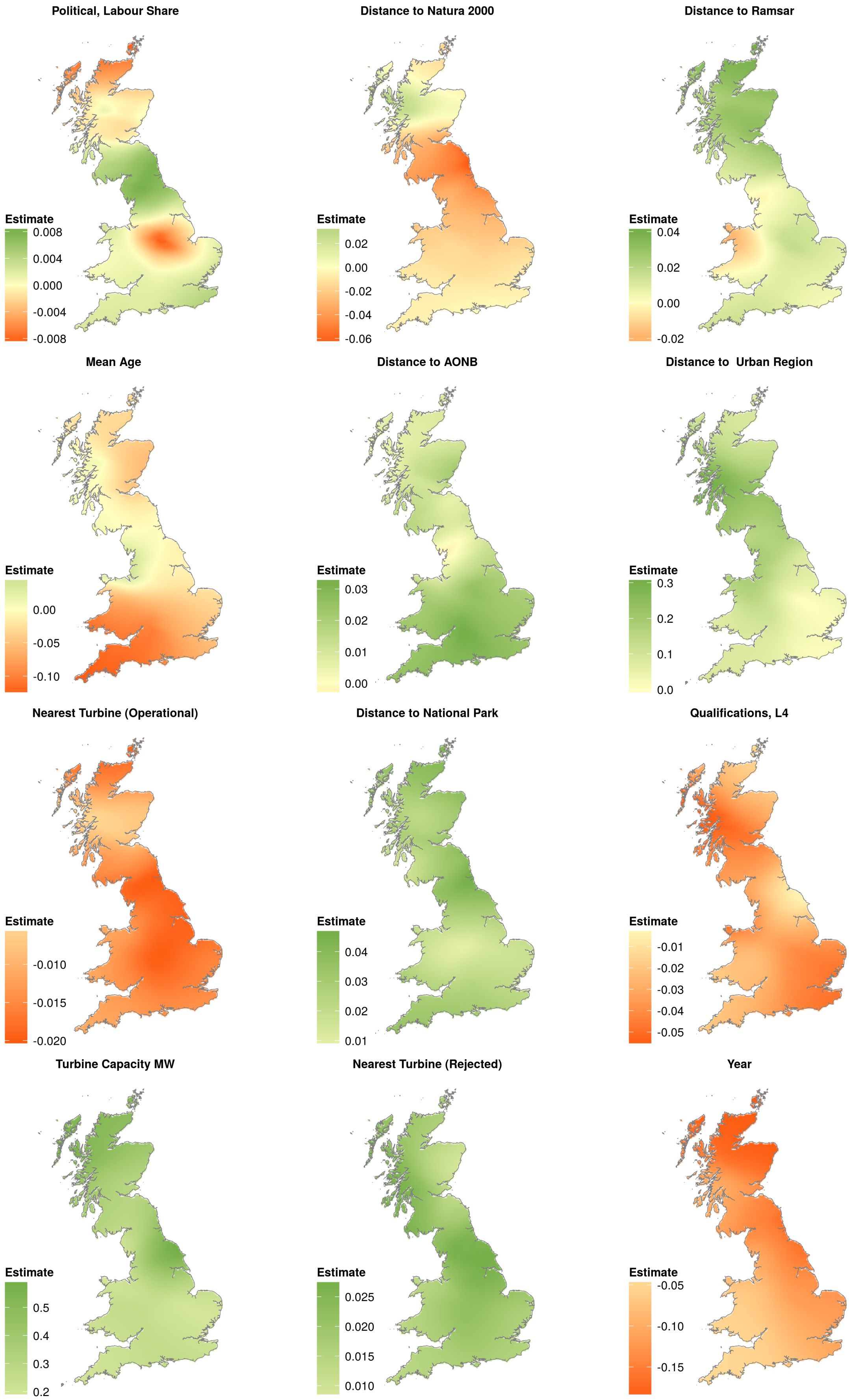


Figure 8.9: Results of the Geographically Weighted Regression parameters.

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 (Jones & Richard Eiser, 2010; Langer et al., 2016). However, it should be noted that these influences have a relatively low impact, despite literature suggesting that 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 (Horst & Toke, 2010) that developers were *"keen to avoid relatively privileged communities and target areas where people are thought to less likely put up a fight"*.

For political variables, the percentage of local council authority control for Labour appear significant. While there is limited research exploring political views and support for wind turbines, it had been expected that there would be a level of correlation that may result from the Conservative party, as their party has generally opposed the building of wind turbines (Smith, 2016). In addition, other studies have highlighted that voters of Labour and the Liberal Democrats are personally more in favour of onshore wind (Populus, 2005), which may result in less local objection against projects in areas where they have stronger support.

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. As shown in Section 4.3.2, this "proximity hypothesis" has been a contentious subject challenged within literature (Eltham et al., 2008; Ladenburg & Dubgaard, 2006; Meyerhoff et al., 2010). 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 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. An assessment of these technical limitations forms part of the analysis in Chapter 9.

Regional Variations

The split data model developed suggests that there are varying influential parameters within England Scotland and Wales, although the reduced number of observations used to build each model increases the uncertainty substantially as indicated by the confidence intervals. Parameters including *Turbine Capacity*, *Wind Speed* and *Distance to Urban Regions* show differing relationships for each country. This suggests that there may be differing motives for projects within each country as well as differential planning constraints. For example, sites in England appear more sensitive to AONB and National Parks than in Scotland and Wales, and supports research that national level government decisions can influence the local developments (Langer et al., 2016).

The geographically weighted model developed in Section 8.2.4 highlights that the local suitability of models should not be overlooked, as there are large amounts of regional variation within the parameter β estimates. As an example, the model suggests that demographics such *Mean Age* have a higher influence within the South of England. There is often a desire to build large, national scale models (Baseer et al., 2017), but it is clear that local context is crucial. This supports the literature that indicates that a local understanding is crucial for accurate modelling (Devine-Wright, 2005a), and such results could be used to better inform local planning decisions.

Several statistically significant parameters exhibit little regional variation, including the *Distance to Nearest Turbine*, *Year* and *Turbine Capacity*. It is interesting to note that the proximity to turbines holds a global relationship, as it had been suggested in previous studies that regions in South West England were generally more supportive of wind energy if they had existing exposure to such projects (Jones et al., 2011; Moller, 2006). To see that such relationships are valid globally can enable these findings to be used to help inform national policy.

8.3 Predicting Site Suitability

It was shown in Section 8.2 that a logistic regression model was developed to assess the influence of geospatial characteristics on the success rate of wind energy planning applications. In this section, the results from the analysis were used to spatially forecast the outcome of future planning outcomes.

It should be noted that this section does not consider whether a site is feasibly developable, but only focuses on the likelihood of a project being accepted. This analysis is integrated into a full decision-making model within Chapter 9.

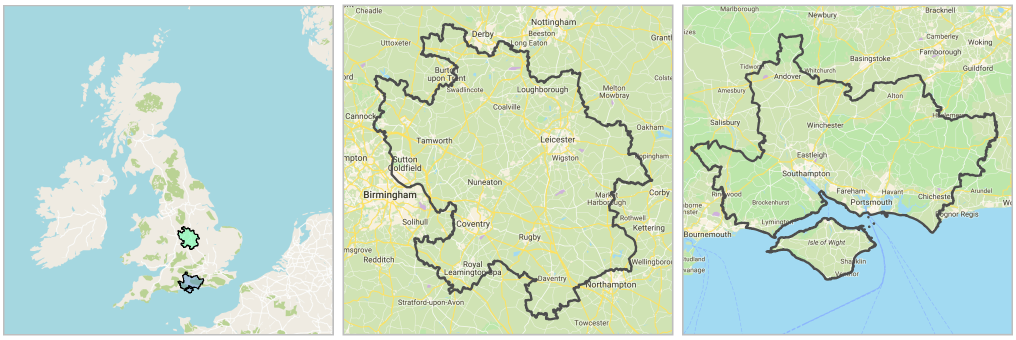
8.3.1 Model Development

Spatial regression models can be used to generalise the findings of statistical analysis, and are frequently used within geospatial modelling (Ward, 2008). Three main models were developed in the previous section: 1) *global parsimonious* model; 2) *regional* model and 3) *GWR* model. While the GWR model was shown to be the technically most suitable model, there are several concerns surrounding the use of this model for the spatial prediction:

- For the added complexity, the GWR only led to a marginal improvement in the model accuracy compared to the *global* model.
- The varying β coefficient for each parameter make it difficult to compare the results between different regions.
- Logarithmic transformation made within the formula makes it difficult to infer the influence that each individual parameter has on the likelihood of planning success. There is additional complexity and computational requirements to generate a predicted GWR model for a large geographic area. Regression models must be interpolated between the sample points.
- The main packages for GWR (*spgwr* (Bivand & Yu, 2017) and GWmodel (Lu et al., 2017)) are unable to conduct spatial predictions for logistic regression models.

Due to these concerns and limitations, the model was built using the *global parsimonious model*. This model contained 12 variables, two of which were non-spatial parameters, *Turbine Capacity* and *Year*. To include these within the prediction, fixed values were assumed, with a Turbine Size of 2MW (the average size of wind turbines in 2016 as shown in Section 3.2.2) and predictions made for the year 2017.

In order to gain a local understanding of the suitability of the model, case study areas were selected to conduct detailed comparative analysis. Two regions were selected, the *Midlands* (centre 52.52N, -1.47E) and *Solent* (centre 50.91N, -1.4E), as shown in Figures 8.10b and 8.10c respectively. These regions broadly represent the LEP regions, although slight adjustments were made to the Midlands region to ensure a similar sized area as the Solent Area to aid comparison.



(a) Overview Map (b) Midlands Region (c) Solent Region

Figure 8.10: Analysis Extent and regions selected for case studies.

The two study areas were selected for several reasons:

- The regions are similar size (4173km and 4214km^2 respectively) with a mix of rural and urban areas. Solent region covers an estimated population of 1.1 million, while the Midlands region has a population of 1.3 million (ONS, 2017).
- Both regions have extensive rural areas which have been considered for wind resources in previous developments; there are, however, large differences in the number of wind turbines actually deployed, with no wind turbines in the Solent region while 30 projects have been constructed within the Midlands region (DECC, 2016c).
- The author has local knowledge of the Solent region and knowledge of projects which have been proposed in the area. Such an insight is important to be able to explore the local context of the modelling results.

To further explore the regional variation, a selection of planning decisions for wind energy developments within the Solent area were reviewed, with a total of 8 projects considered. This provided a way of assessing the predictive results against a sample of previous sites within the region.

Predictions of site acceptance were made across the study region at a resolution of 500 metres, which was selected as it is the recommended minimum spacing between commercial scale onshore wind turbines (Smith, 2016). The predictions were generated using the *stats* package in R (R Core Team, 2017).

8.3.2 Results

The resulting site acceptability maps are shown in Figure 8.11, providing a prediction of the likelihood of a project receiving planning acceptance. The global average acceptance rates for the overall model was 20% with the range of individual sites from 2 to 90. Only 0.9% of sites scored greater than 50% site acceptability, with 75.7% of locations estimated of having less than 25% chance of acceptance.

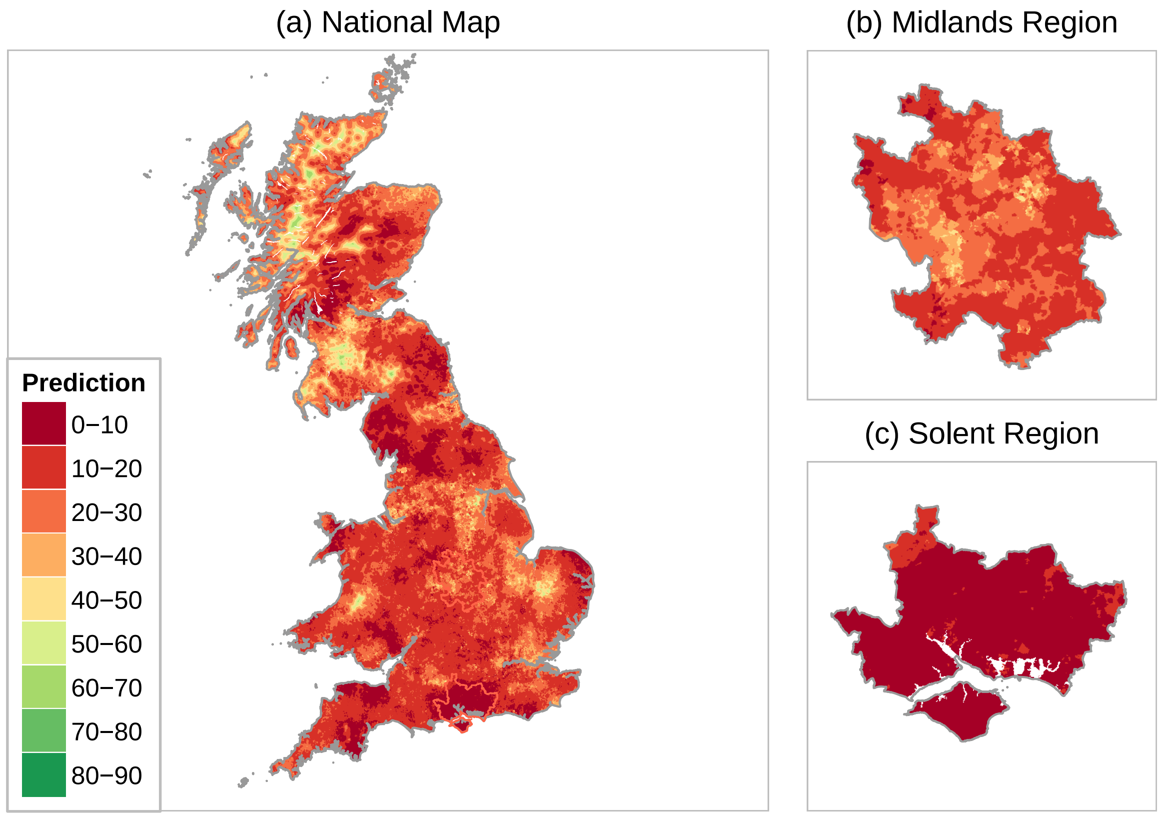


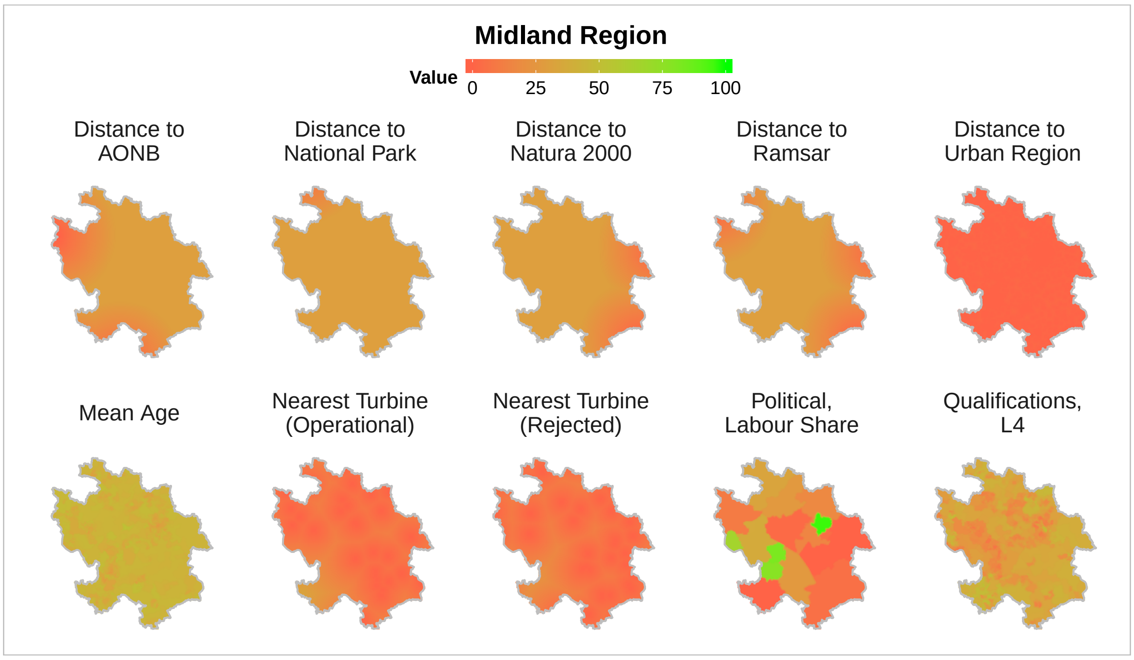
Figure 8.11: Maps highlighting the likelihood of wind energy projects receiving planning permission, as derived from the parsimonious logistic regression model. A turbine size of 2MW was assumed, and predictions were made for the year 2017.

A detailed breakdown of the regional case studies against the national average is shown in Table 8.6. No site within the Solent area is rated higher than 25% chance of acceptance. The Midlands region appears more suitable, although again no region exceeds a 50% estimated chance of planning success.

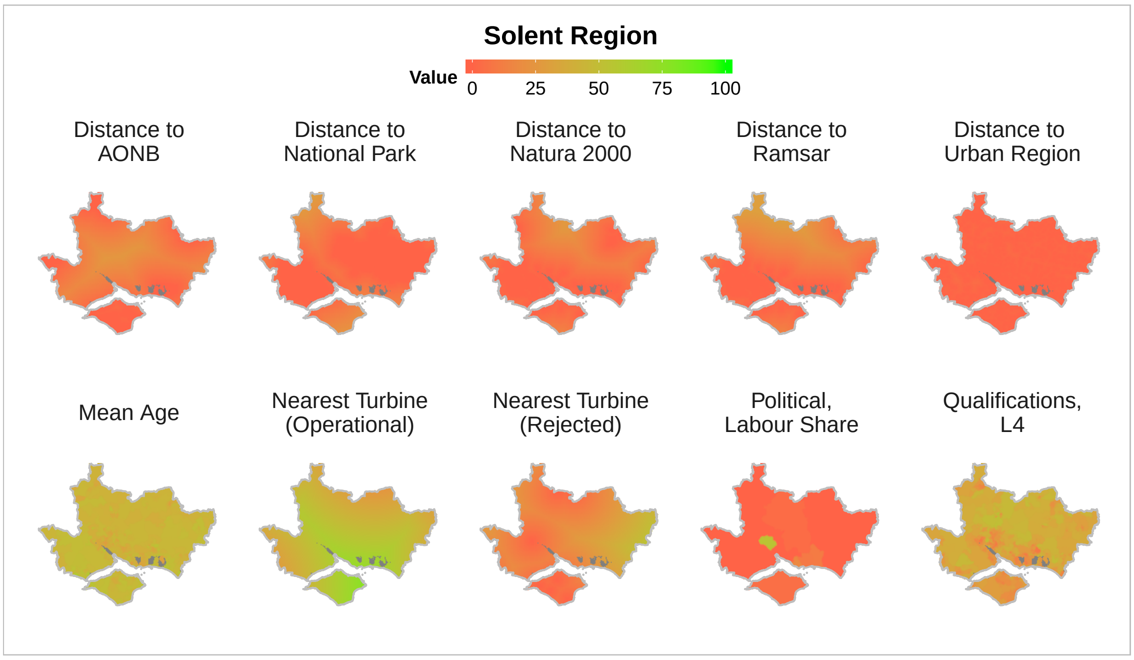
Table 8.6: Summary statistics comparing region suitability of onshore wind within the study regions

	mean	sd	median	min	max	skew	Area
GB	0.20	0.09	0.18	0.02	0.89	1.08	228433
Midlands	0.20	0.06	0.19	0.08	0.43	0.77	4216
Solent	0.06	0.02	0.06	0.02	0.25	1.74	4164

Detailed results are presented for the two cases study areas in Figures 8.12, highlighting the value of each variable within the two study regions. These can be combined with the knowledge of odds ratios as shown within the statistical modelling to infer the determining factors of suitability within each region, as will be discussed further in Section 8.3.3.



(a) Parameter layers for Midlands region.



(b) Parameter layers for the Solent region.

Figure 8.12: Predicted outcome and variable mapping for the cast study regions.

8.3.3 Discussion

The national prediction raster shown in Figure 8.11a 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 20%, which is below the rate of acceptance of wind energy in the UK, which was 40% in 2016 (DECC, 2016c). 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 (Smith, 2016). Therefore, sites which are generally opposed before planning will often be abandoned before being taken to planning permission.

The analysis results highlight that there is no "one-size-fits-all" approach, 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 (Stoddart & Turley, 2012). Chapter 9 therefore explores the implication of these findings on the resource potential of onshore wind.

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. Studies have however noted that the region has a higher level of wind energy support in the region (Eltham et al., 2008).

Case Studies

Despite the Solent and Midlands being similar in area and population, the model indicates large differences in the acceptability of wind energy. On average, the results suggest area that projects are 14% more likely to receive planning within the Midlands than in the Solent. To explore the cause of this difference, the layer values shown in Figure 8.12 can be combined with the parameter influence expressed within the Odds Ratios in the Section 8.2.2 to determine influential parameters. The following regional difference can be observed to explain the difference:

- **Nature and Landscape Designations**: 24% of the Solent region contains National Parks or AONBs.[6] The proximity to such sites lessens the chance of project approval.
- **Demographics**: The demographic composition within the Solent region is generally higher qualified, with a higher mean age. Both these factors were suggested to reduce the chance of planning approval.

[6] New Forest, South Downs National Park, and AONBs on the Isle of Wight

- **Labour council share**: the statistical model indicated that increased level of labour counsellors resulted in higher acceptance of wind energy. The Midlands region has a high coverage, while there is a low representation within the Solent region which is largely Conservative led.
- **Proximity to existing wind energy projects**: For regions in the Solent area, there are no existing turbines in the study area, with the nearest project over 50km from the region, while a number of projects have been rejected planning permission in the region. In comparison, there are 30 active projects within the Midlands region, with greater proximity to sites permission.

Within the review of planning applications of projects proposed in the Solent region, it was consistently found that the AONB and landscape designations were cited as reasons for their rejection (Isle of Wight Council, 2010; Test Borough Council, 2013). There is difficulty in observing any direct relationship between political and demographic variables, as these in themselves cannot be used to refuse the planning decision. However, as discussed previously, these variables are argued to have an indirect impact on the planning process through more effective campaigning against projects.

The statistical model indicated that *Labour council seat share* positively influences the acceptance of wind energy projects, and it can be seen within the Midlands region that there are areas with 100% representation. However, it can generally be observed that Labour voters are concentrated in urban areas (Dunleavy, 1979), and this view was supported within the preliminary data analysis in Chapter 8.1, which highlighted the spatial correlation between Labour voters and Large Urban areas. While wind energy may be more acceptable in these population groups, it is unlikely that suitable sites for development will be found due to the land requirements which are not necessarily available in urban areas. This therefore highlights the importance of integrating the results of this sensitivity modelling with traditional onshore wind GIS approaches to identify sites which are both socially acceptable and feasibly developable, a topic which is explored further within Chapter 9.

8.3.3.1 Application of Findings

While the model provides useful regional insights, it was shown within Chapter 8.2 that the overall model fit was relatively low, with a Psuedo R^2 value of 0.19. However, with the estimated cost of planning applications for commercial scale projects exceeding £50000 (Renewables First, 2016), 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.

As highlighted within the literature, there have been recent changes in legislation regarding the planning of wind energy. These grant greater controls to local communities to oppose the development of wind turbines (Smith, 2016). Such changes in planning likely have an effect on the underlying influences of wind energy acceptance rates, and therefore care is required forecasting the results of a model based on historic data into future predictions. However, such approaches still offer a useful insight for high-level regional forecasting.

8.4 Conclusion of Acceptance Rates Analysis

This chapter investigated the influence of geospatial, environmental, demographic and political attributes on the probability of wind farm planning approval in Great Britain between 1990 and 2017. Four regression modelling techniques were developed and iteratively refined to improve the overall suitability of the model.

The findings of this work reveal that local demographic and political parameters appear to influence the planning outcomes of projects, and that many of the geospatial parameters typically integrated into wind energy models appear insignificant in determining site approval. To the authors' knowledge, such quantitative findings have not previously been demonstrated for onshore wind, and support the conclusions existing qualitative studies.

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 (Smith, 2016), there may be a clear limitation 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 (Malczewski, 2004; Toke, 2005), 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) (Toke et al., 2008; Warren & McFadyen, 2010; Wolsink, 2000).

A number of statistically significant parameters were identified within the research. The results appear to confirm existing literature by indicating that the distance to urban areas positively affects acceptance rates: however, there is a large amount of uncertainty as can be seen in the error bars. It is also interesting to note that socio-demographic characteristics have been indicated as being significant: the model suggests that regions with higher mean age and qualifications are less accepting of wind energy.

While the models have indicated a range of significant relationships, there are concerns surrounding the overall model fit, with relatively poor R^2 values and predictive accuracy. This clearly reflects the concerns raised within literature that geospatial tools in isolation fail to accurately model the local challenges within renewable energy development (Malczewski, 2006b; Strantzali & Aravossis, 2015). These findings suggest that geospatial modelling techniques should not be considered entirely in isolation, and that they are best combined with the development process of wind energy. For example, it was shown in the literature review that projects proposed by local communities are generally more accepted than those proposed by large energy companies (Toke et al., 2008).

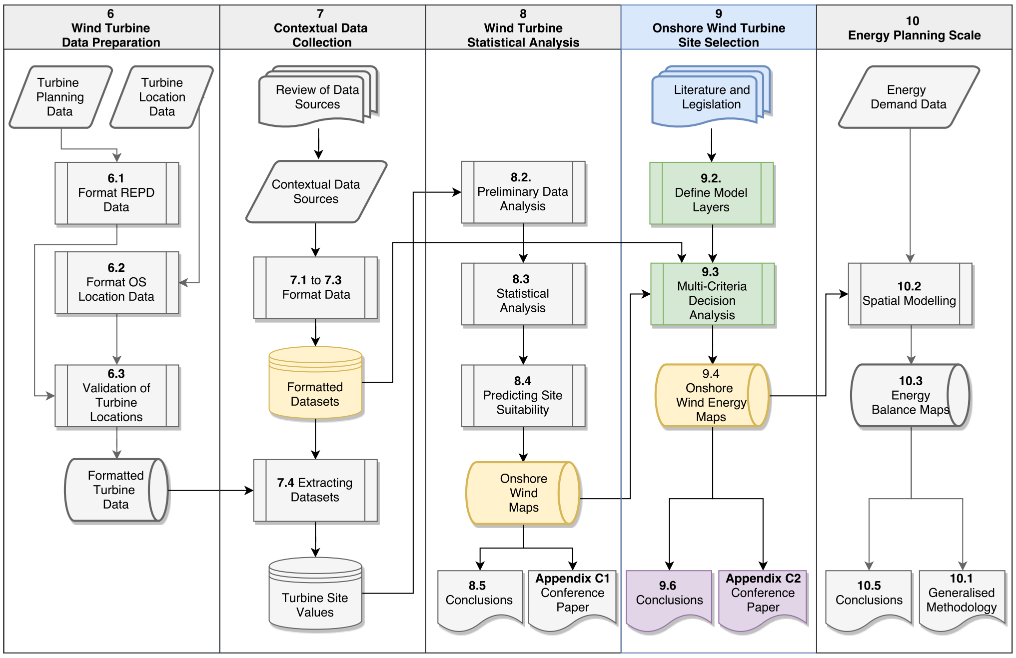
In isolation, the results of this chapter are limited in their direct applicability for locating suitable sites for development, as the chance of a project receiving planning permission is just one aspect of a complex selection criteria for wind energy. The results of this chapter are therefore integrated with MCDA techniques in the following chapter to identify locations for development and assess regional capacity estimates.

Chapter Summary

- Preliminary data checks identified several issues with the dataset, with missing data being replaced, and censoring conducted to limit extreme values.
- Key parameters which influence the acceptance rates of wind energy include 1) Turbine Capacity; 2) Year of Construction; 3) Demographic variables (mean age and level of qualifications) and 4) Political variables.
- Analysis suggests that proximity to existing wind energy developments increases the chance of a project being successful, countering the tradition "*proximity hypthesis*" proposed by literature.
- The model accuracy at predicting wind energy acceptance rates is relatively low with an overall model fit of 0.2, highlighting the importance of non-geospatial parameters within modelling.

Chapter 9

Onshore Wind Turbine GIS-MCDA



The research has so far focused on exploring the sensitivity of wind energy planning applications. However, they provide no indication as to whether a wind project should be built in the given location considering technical and economic parameters. This section therefore builds upon the analysis presented in Chapter 8 to present a geospatial model which can be used to identify suitable locations for development and assess regional capacity for onshore wind energy. The chapter is broken into the following sections:

- to outline the development of the onshore wind GIS model.
- to explore the difference in development opportunities within case study regions.
- to identify potential capacity limits for the UK onshore wind development.

Overview

An overview of the stages of the analysis is presented in Figure 9.1, highlighting the overall structure of the GIS modelling and decision making process. This is explained in detail within the following subsections.

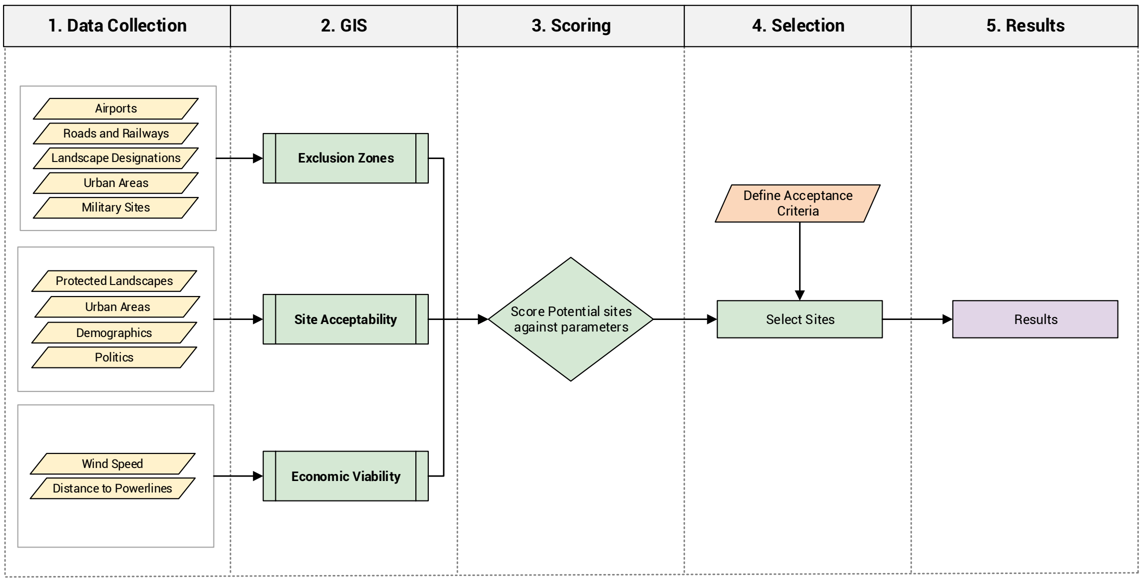


Figure 9.1: Schematic of the GIS-MCDA analysis within this chapter for assessing onshore wind site suitability.

9.1 Research Context

It was highlighted within the literature review in Section 4.2 that there have been a large number of geospatial models developed for assessing the suitability of sites for wind energy installation, with models typically using Multi-criteria Decision Analysis (MCDA) to identify the suitability of sites (Baban & Parry, 2001; Watson & Hudson, 2015). However, a number of concerns were raised for these existing modelling approaches:

1) **Assessment of Site Sensitivity**: GIS models are largely driven by a developers perspective, and have not directly inferred the chance of a wind farm being granted planning permission. The work from Chapters 8.2 and 8.3 has helped to identify what might influence a wind farm being accepted, but it has not considered the overall site suitability.
2) **Combination of non-commensurate data** To create a single site suitability score requires the combination of a range of economic, environmental and social parameters which cannot directly be summed together into a single scale. Methods such as the linear transformation method are often used to standardise each variable, but there is limited empirical justification for such approaches (Jiang & Eastman, 2000).

This approach builds upon the analysis presented in Chapter 8.3, and demonstrates an alternative layered approach combining non-commensurate parameters, in particular avoiding the use of linear transformations within the MCDA.

9.2 Model Layer Definition

To overcome the limitation of existing MCDA studies, a layered model approach was used to separate non-commensurate datasets. Instead of combining variables into a single score, the suitability of sites were scored against three aggregated variables:

1. **Exclusion zones**: legislative and technical restrictions which prevent the construction of a wind turbine.
2. **Economic viability**: financial return of the potentail site.
3. **Social acceptability**: likelihood of the site receiving planning permission.

Exclusion Zones consider whether the site would technically be suitable for development. This was based on several sources of information: firstly, existing legislation and ecological guidance as discussed within the literature review. However, it was observed that there are few strict rules of where developments are allowed: for example there is no legal specification for the minimum distance between a house and a turbine (Langer et al., 2016). The existing development patterns of wind energy projects was therefore assessed to identify whether specific regions were avoided by developers. Based on this research, the following taxonomy was developed to categorise the types of exclusion criteria:

- **Hard Planning Criteria**: legislative restrictions that prevent the development in specific areas. For example, wind turbines must not be built within a toppling distance of main roads. These were explained within the Literature Review in Section 3.2.
- **Soft Planning Criteria**: areas where there are no legislative restrictions but are generally avoided by onshore wind developers. These were derived from statistical analysis of existing wind energy planning applications. As an example, it is technically possible to build in National Parks, however only two projects have been built within them, and therefore they are largely considered as non-developable areas.
- **Buffer Criteria**: areas nearby sensitive features which are generally protected from development. While the site itself may not be designated, this explores whether there is any geospatial trend for sites to be located away from certain features. For example, wind turbines sites are not banned near airports or nearby national parks, however these areas are frequently avoided by developers.

The derived values are presented in Table 9.1. Based on these three categories, three scenarios were formed to assess the impact of planning restrictions on the development potential: 1) *Low Restriction* (Hard Planning Criteria only) 2) *Medium Restriction* (Hard & Soft Planning Criteria)

Table 9.1: Parameters and exclusion distances used within the model.

	Exclusion Distance, km		
Parameter	Hard Planning Criteria	Soft Planning Criteria	Buffer Criteria
Airports	0	2.00	10.00
Roads	0.15	0.15	0.15
Railways	0.15	0.15	0.15
Military Sites	-	0.00	10.00
Urban Areas	-	0.00	2.00
Powerlines	0.15	0.15	0.15
Landscape Designations [a]	-	0.00	2.00
Nature Designations [b]	-	0.00	2.00

[a] National Parks, Areas of Outstanding Natural Beauty, Heritage Coast
[b] National Nature Reserves (NNR), Natura 2000, Special Protection Areas (SPA), Sites of Special Scientific Interest (SSSI)

and 3) *High Restriction* (Hard, Soft and Buffer).

Economic Viability of the site assesses the potential cost effectiveness of a wind energy project. For wind projects, this is influenced by the 1) *Wind Speed* 2) *Distance from national grid*; 3) *Site access* and 4) *Ground clearance* (Van Haaren & Fthenakis, 2011). For the study region, it was considered suitable to only use the first two parameters, as site access and ground clearance are primarily only issues in more sparsely countries. Annualised wind speed data was used (DTI, 2001), and logarithmic height transformations were used to account for the height of the wind turbine. The power curve for a typical 2MW wind turbine (Vestas, 2017) were used to calculate the energy yield based on a given wind speed.

Finally, **Social Acceptability** was based upon the analysis from Chapter 8, and predicts the likelihood of a project receiving planning permission. This is based on the generalised statistical model presented in Figure 8.11.

9.3 Multi-Criteria Decision Analysis

A challenge with MCDA is how to compare non-commensurate datasets to create a single. Existing models often merge criteria which influence different quantitative scales. For example, the developer is primarily interested in the economic viability, something which can be measured by a cost, while the public may prefer locations which are more remote and have a lower visual impact on surrounding landscapes.

In order to overcome the issues of faced by non-commensurate datasets, a multi-dimensional approach was used to prevent the combination of contrasting datasets. As shown in Figure 9.2, each site is categorised based on its Economic viability (X-axis) and Site Suitability (Y-axis), with four types of suitability defined (Low/Potential/Good/Excellent).

It is argued by the author that the cost is a less dominant factor compared to planning permission in the UK, and therefore a lower cut-off point was selected for the analysis of this value. This supports evidence in the UK that onshore wind speeds in the UK. The analysis selected sites based on their suitability rating. To estimate the potential capacity of sites that could be developed, all sites that score "*Excellent*" or "*Good*" were selected as suitable for development.

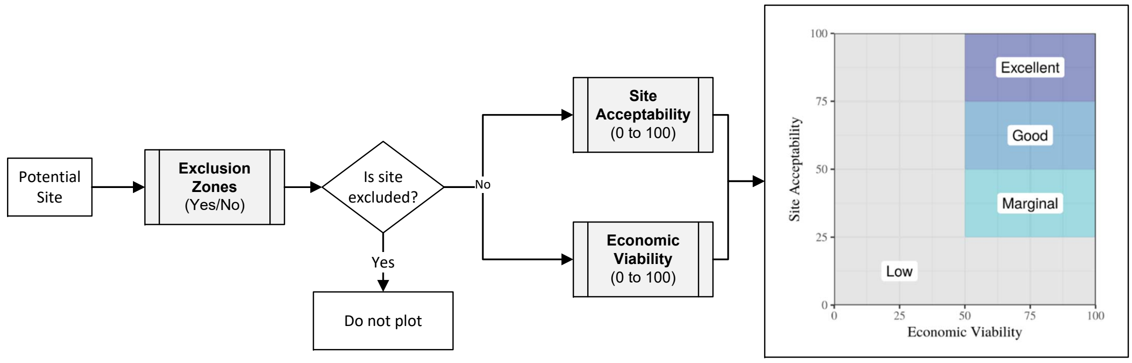


Figure 9.2: Classification of potential sites based on the GIS layer results.

9.3.1 Selecting Sites

Two methods were considered to identify suitable sites within the methodology:

1. **Thresholding**: criteria were set for minimum acceptability for cost and site sensitivity. Sites which met a minimum criteria for the two parameters were deemed suitable for development. There would be no attempt to rank the solutions as the cost and site sensitivity parameters would not be directly compared.
2. **Ranking**: the sites are scored on the total suitability. Sites could be compared by defining a single-dimension suitability score which combines Economic Viability and Public Acceptability. However ranking sites on a combination of the economic and site sensitivity data requires the combination of non-commensurate data.

As the key driver for the model is resource capacity assessment, it was decided that the threshold approach was more suitable. It was therefore decided that any site with a score of "*Marginal*" or better was considered as a suitable site for development.

9.4 Results

The results from the three separate geospatial model layers are presented in Figure 9.3. These layers are combined to determine the site suitability score displayed under the medium development restriction scenario, as shown Figure 9.4. Nationally, it can be seen from the results that sites appear to be more suitable within Scotland, the South West of England, and patches of West England. For the Solent region, 81% of the land was excluded with no sites being deemed "*Good*" or

"*Excellent*" for wind development. In comparison, only 36% of the Midlands region was excluded for development.

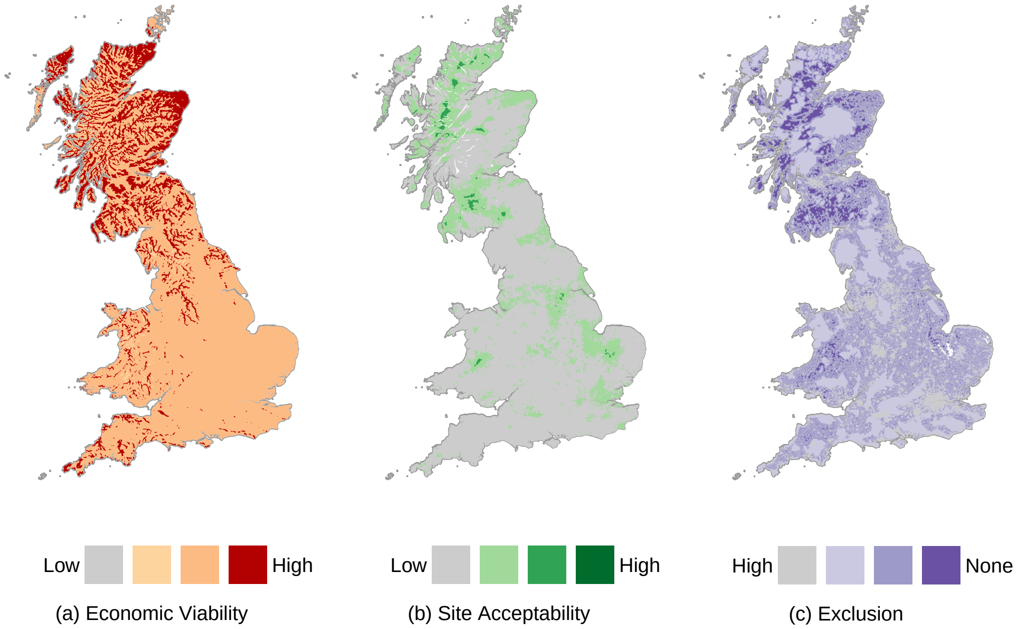


Figure 9.3: Results for the GIS layers from the Onshore wind GIS-MCDA model.

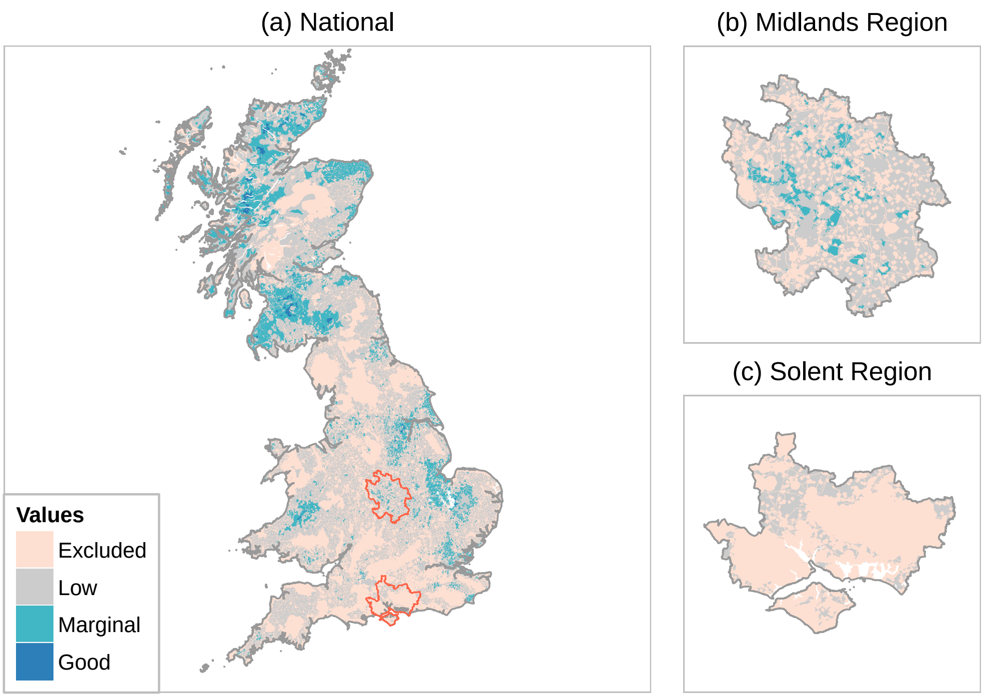


Figure 9.4: Site suitability results from Onshore Wind MCDA model, under the Medium Restriction Development Scenario.

Table 9.2 provides a cross-tabulation of suitability scores against the exclusion criteria, to assess the impact of each of the three exclusion regions on national development patterns. Sites assessed higher than "Good" and outside of "Soft Criteria" were considered as potentially suitable for development. Such sites cover 0.85% of the country, and if fully utilised (assuming turbines are installed in all suitable sites at a density of 8MW/km^2), would result in a potential capacity of 16GW..

The comparative suitability of the regions can also be explored through two-dimensional density plots as shown in Figure 9.5. Each non-excluded site is represented as a point, and the regional variation in acceptability and economic viability can be viewed on separate scales. The site acceptability within the Solent region is generally less than the national average and the Midlands, although the economic viability is generally similar.

Table 9.2: Site score suitability matrix comparing exclusion criteria against site suitability, coverage of land covered by each classification

	Exclusion Criteria				
Suitability Score	Hard Criteria	Soft Criteria	Buffer Criteria	No Exclusion	Total
Low	13.21	29.72	30.92	2.44	76.29
Marginal	4.12	6.6	8.89	3.23	22.83
Good	0.03	0.41	0.28	0.16	0.88
Excellent	0	0	0	0	0
Total	17.36	36.73	40.08	5.83	100

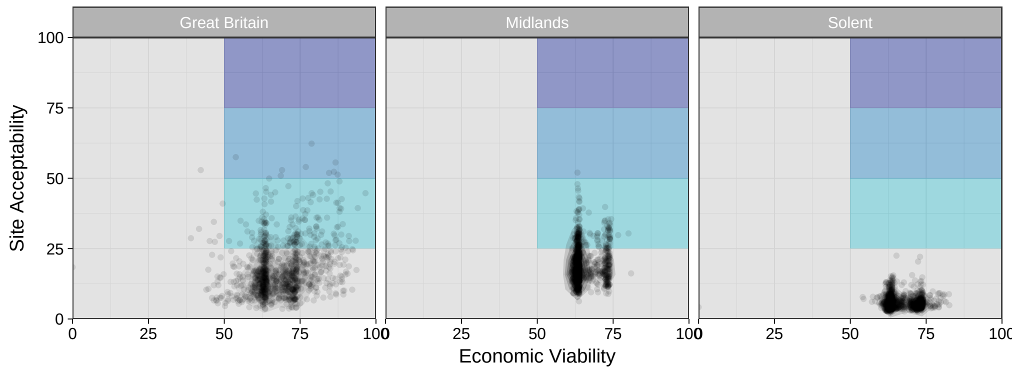


Figure 9.5: Two-dimensional density plot comparing regional site suitability.

9.5 Discussion

The analysis suggests that 16 GW of onshore wind would be highly suitable within a medium development restriction scenario, which considered the "hard" and "soft" planning criteria. If the stricter "buffer" criteria are met, the estimated capacity is reduced to 8 GW. Both these estimates are significantly lower than previous studies which have suggested total capacity could exceed 200 GW (Gove et al., 2016a; Stoddart & Turley, 2012). This highlights the impact of considering likelihood of planning acceptance within the GIS-MCDA and the constraint this places on development.

It was shown in Section 2.5 that there is 9GW of installed onshore wind energy in UK, 8GW of which is within Great Britain. Based on the estimates from the model, the existing onshore wind capacity could be doubled, and would increase the share of renewable energy generation by 25%. This would provide a significant contribution to renewable energy targets.

The case studies of Solent and Midlands highlight the regional variations in onshore wind potential resource as shown in Figure 9.4, and builds upon the evidence presented in the previous chapter. From a resource perspective, the Solent area is highly suitable with many hilly regions and its coastal location results in high wind speeds. However, the opportunity for development is limited by National Parks and AONBs, and the sites that are located outside of these regions are largely unsuitable for development due to the demographic composition. In comparison, the the Midlands region faces much less restriction in where developments could be made and presents much greater opportunity for future development.

The results further highlight that cost is not the dominant issue in determining the suitability of a wind energy site, as wind speeds are largely satisfactory and in Great Britain most sites are an acceptable distance to powerlines for a wind turbine to be economic. A number of previous studies have placed a high weighting on wind resource (Shirgholami et al., 2016), reflecting the interest of the developer to maximise returns. In reality, it may be in their interest to select a less windy site that is more likely to receive planning permission.

On a national level, it is important to consider the distribution of potential sites and the consequent impact this may have on the electricity transmission network. The results indicate that regions in Scotland are most suitable for further development; however, such areas are distant to large load centres such as cities, requiring transmission networks or energy storage to be upgraded (National Grid, 2017).

It was seen that there are large amounts of variation within the UK, with Scotland being highly suitable compared to many parts of England and Wales. This is further highlighted by Figure 9.6, with the treemap comparing the area of administrative regions against the estimated resource potential from the model. The graph highlights how there is a disproportionate availability of resource in Scotland, and how a select number of administrative areas have access to a large proportion of the wind resource. In particular, the Highlands, Dumfries and Golloway and Aberdeenshire over 30% of the national wind resource, despite covering only 19% of the land area.

A benefit of building the model into several intermediate layers, such as used in this model, is that it allows the results to be more easily interpreted and minimise the concerns surrounding standardisation of parameters. When combining the variables into a single suitability score, it can easily hide or distort what is influencing the site score, and make it difficult to understand why some sites are more suitable than others are.

Whilst the analysis has tried to understand the chance of a project being accepted, it has only considered those which can be geospatially modelled. As previous studies have highlighted, such parameters in themselves only provide part of the explanation as to why wind farms are accepted (Langer et al., 2016; Toke, 2005). Greater emphasis must also be placed on the planning process and local engagement of a wind project if it is to be successful at planning. The analysis has also

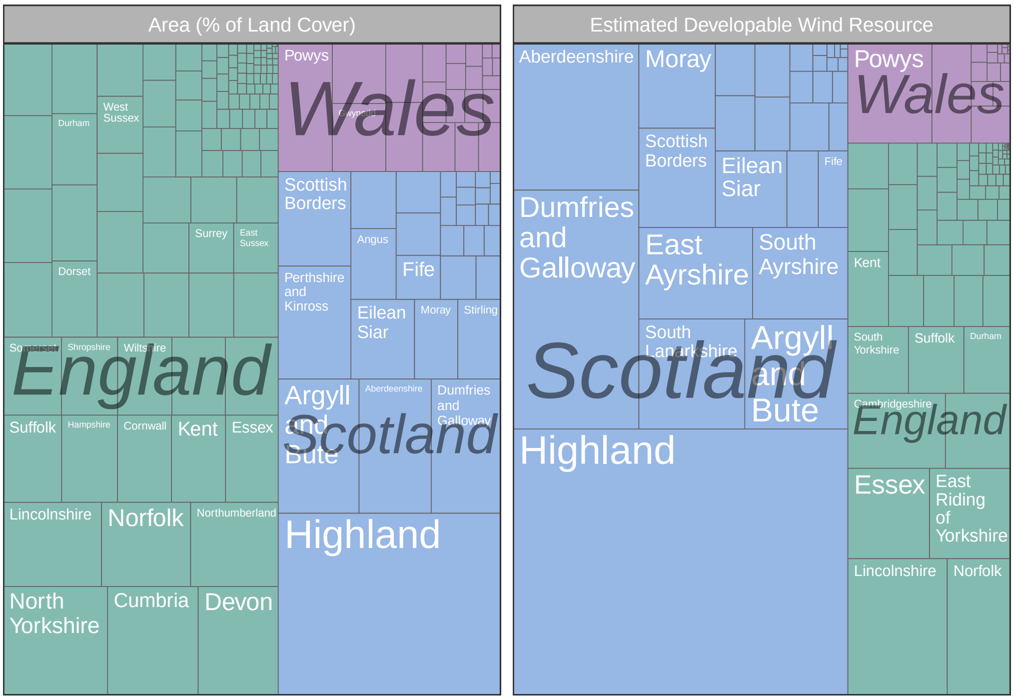


Figure 9.6: A treemap comparing the area against the estimated resource for Counties within the United Kingdom.

not considered the impact of electricity transmission networks, and the potential requirement of grid reinforcements. It is already being seen in the UK that grid reinforcements are being made to transfer electricity and this is becoming a limiting factor in the development of renewable energy projects (National Grid, 2015). The majority of sites identified as suitable for development are distant from large load centres, and therefore would place additional strain on the transmission network to transfer this electricity across the country. It is therefore important that this issue is explored further in future analysis.

The model only considers the suitability of individual wind turbines, and does not assess whether an area is suitable for development of a larger wind farm. There would be economies of scale in proposing a single larger development, and as such, these locations would be preferential to developers.

The analysis did not consider the influence of the cumulative number of wind turbines within a certain area. It is not fully understood within literature whether there is a limit to the development potential of wind turbines, although some evidence suggests that regions can reach a saturation level (Moller, 2006; Toke et al., 2008).

9.6 Conclusion

This chapter has presented a GIS-MCDA which can be used to assist in locational planning of onshore wind turbines. By integrating planning acceptance rates into the decision-making process, the results of this model have highlighted that the potential resource is significantly lower than previous estimates. However, there remains an opportunity for further development of onshore wind turbines to help meet renewable electricity generation targets.

The GIS-MCDA presented an alternative method of combining non-commensurate data into the decision-making process. By avoiding the use of standardisation, there is less distortion to the input data and this reduces potential errors within the model results. This also provides greater insight into the model results as it is easier to understand the factors influencing site suitability.

Using two case studies, the results have shown how the onshore wind capacity can vary significantly for similar types of regions within the same country. This can be influenced by physical restrictions such as landscape and nature designations, or "hidden" factors such as local demographics and political composition. It is therefore important that these factors are understood when wind energy projects are being considered within a region.

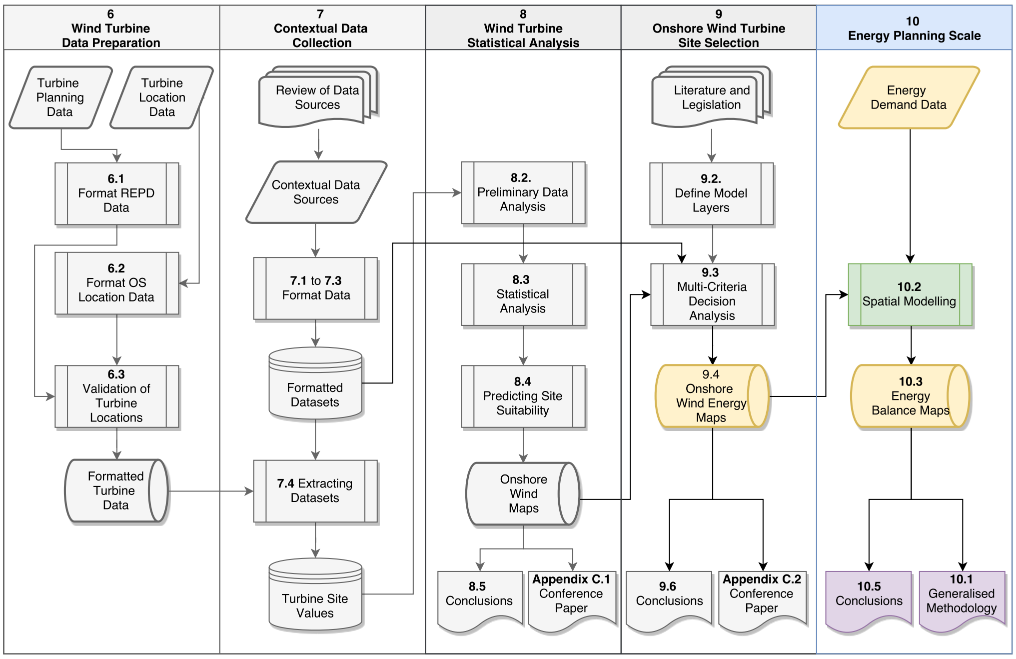
The findings of this analysis can be used by a range of stakeholder to improve the planning and development of wind energy projects. As examples, regional planners could more accurately estimate the potential capacity within their region, and project developers could gain a greater understanding of where sites should be proposed to increase the likelihood of receiving planning permission. The results should support, not replace, local level planning.

Chapter Summary

- GIS MCDA model built to integrate planning acceptance analysis, as shown in Chapter 8.
- A layered approach was developed to consider legislative, economic and planning acceptance separately to address concerns surrounding non commensurate data.
- Capacity estimates are indicated to be within a range of 8 to 16GW. This figure is well below previous estimates, with estimates of 200GW being suggested, and is largely due to the consideration of social acceptance reducing areas in which wind energy is developable.

Chapter 10

Energy Neutrality Scale Analysis



The analysis so far has considered renewable electricity supply in isolation of energy demand. However, it was noted previously that the locations where renewable energy supply is high are often not the best for the electricity transmission network (Wilson, 2012). For example, a large proportion of wind resource is in Scotland, and this compounds the already growing pressures to upgrade the national grid to cope with this geographic separation from the major cities in the UK.

Using the results of the onshore wind GIS-MCDA as a case study, this chapter presents a novel approach of assessing the ability of cities to meet their energy demand. The chapter has the following aims:

- to outline the spatial scale analysis methodology for assessing potential energy neutrality.
- to demonstrate the use of wind energy as a case study model.
- to highlight potential areas of conflict within UK regions.

10.1 Background

It was presented within the background literature in Chapter 2 that there have been calls for the broader consideration of spatial scale within energy analysis (Bridge et al., 2013). While the topic of spatial scale has been raised within literature (Frew & Jacobson, 2016; Horsch & Brown, 2017; Oudes & Stremke, 2018), there has been limited consideration regarding the assessment of the suitable planning scale of cities, and to the author's knowledge, no quantitative assessments have previously been conducted which directly assess the impact of planning scale on renewable energy development.

Whilst cities are developing as a key scale for the transition to renewable energy technologies, there are concerns that they have limited resource availability to drive the transition to renewable technologies. In particular, urban areas have limited opportunities for renewable energy resource (aside from building mounted Solar PV) and experience high energy demand. It is therefore argued that urban areas are reliant on their surrounding rural land, termed "*urban hinterland*", which generally have lower levels of energy demand and greater opportunities for the development of renewable energy technologies. These challenges are represented in Figure 10.1. However, it remains unclear how large this surrounding area must be for the energy needs of the urban region to be met.

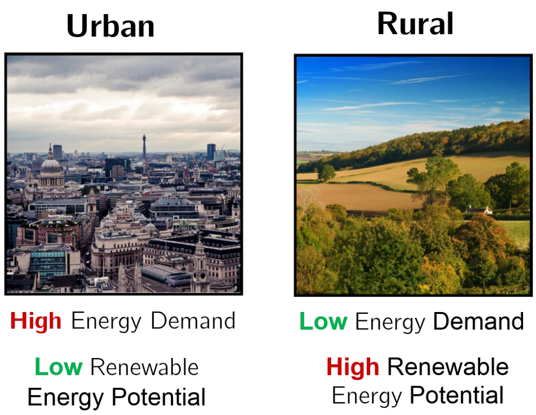


Figure 10.1: The Energy Balance context of urban and rural regions.

It is therefore argued that it is important to understand the scale at which energy demand can be met by available renewable energy resources. Such information would enable the application of the "*Matching Principle*", whereby whereby the scale of the infrastructure challenge should determine the appropriate governance level for responding to it (Butler & Macey, 1996).

10.2 Generalised Methodology

The Energy Neutrality Scale Analysis (ENSA) approach was developed to determine the scale at which energy equilibrium can be met for a city. The overall methodology is outlined within Figure 10.2. By considering large urban conurbations as "hubs", the model seeks to identify the scale at which energy balance between energy demand and renewable resources can be achieved. The full methodology is detailed within this subsection.

Extent and Analysis Locations

It may appear slightly circular in nature, but whilst the model aims to determine the scale of planning, an overall study extent must first be specified for the model analysis. It is recommended that this is conducted at the largest possible scale for initial scoping studies, with the opportunity to further refine the model to determine local constraints later.

Within the study region, cities and towns should be selected for the assessment of energy scale. Whilst the methodology can be run on multiple cities, it considers each location in isolation, and therefore the energy footprint of cities in close proximity may overlap. This is discussed in detail within Section 10.4

Energy Potential Mapping

The potential for each renewable energy technology needs to be assessed for the study region. Energy Potential Mapping (EPM) can be used to generate resource potential maps for the renewable energy technologies considered within the assessment (onshore wind, solar photovoltaic, etc.). Each technology layer must be generated into a consistent resolution, both temporally and spatially, to allow for aggregation of the various layers within the model.

The work presented in Chapters 8 and 9 aimed to highlight the importance of developing detailed EPM models for resource assessment of renewable energy technologies. It is important that these layers accurately reflect not only the technical constraints of renewable energy development, but also consider the broader social and technical restrictions.

The methodology can optionally include marine resources within the assessment (offshore wind, tidal turbines etc.). However, within the UK context, there is strong legislative control over such developments from a national level, as development is controlled by the Crown Estate as explained in Section 2.5. It was therefore decided to not consider such resources within the methodology, instead focussing on land-based technologies.

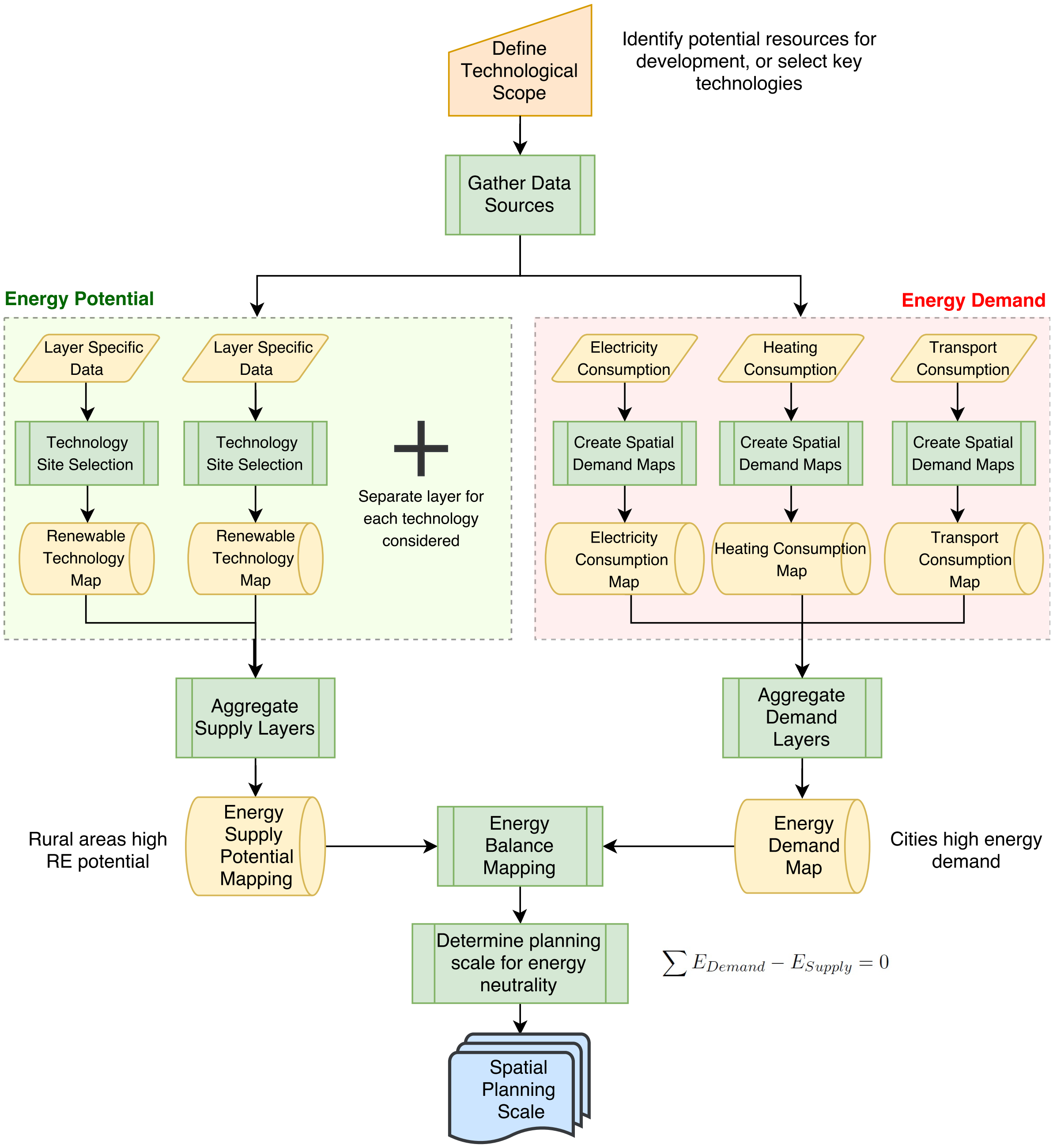


Figure 10.2: Energy Neutraility Scale Analysis, Generalised Methodology.

Energy Demand Inclusion

Energy demand statistics must be collected for the region, and must be spatially disaggregated. It is recommended that data is collected at the finest resolution possible (typically by council ward), instead of regional or county level statistics. This allows for the spatial variation in energy demand to be considered within the model.

Energy Balance

Having determined the potential energy supply and demand for the technologies considered, the aggregated energy balance map layer can be developed. This should be calculated for each cell within the model layer, as conceptualised within Figure 10.3.

The overall aim of this stage in the process is to highlight regions in which there is energy imbalance. This imbalance will largely be a result of the high energy consumption within urban areas, as the peak energy demand within cities far exceeds the renewable energy potential for rural land: as an example, peak wind turbine installation density can generate around 10 GWh/annum/km^2, which provides around 10% of the equivalent energy density required to meet demand in Central London (measured to be 96 GWh/annum/km^2).

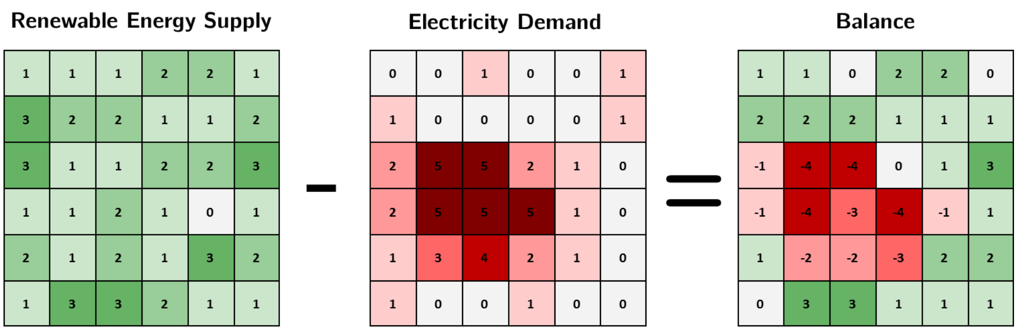


Figure 10.3: Schematic highlighting the calculation of energy self sufficiency within the ENSA methodology.

Scale Building

Two approaches are proposed for the assessment of spatial scale:

- **Radial Approach**: concentric rings are taken from the centre of the analysis region. The energy balance is considered within each ring of the buffer.
- **Boundary Approach**: the existing territorialisation is considered within this, and is based upon the current boundaries within the study region. Starting from the centre of the study region, neighbouring regions are sequentially added to the energy cluster with the energy balance being considered after each stage.

These two separate approaches are demonstrated in Figure 10.4, highlighting the difference in regions considered for the Solent region. It should be noted that as an island, the Isle of Wight is considered as separated in the boundary-based approach.

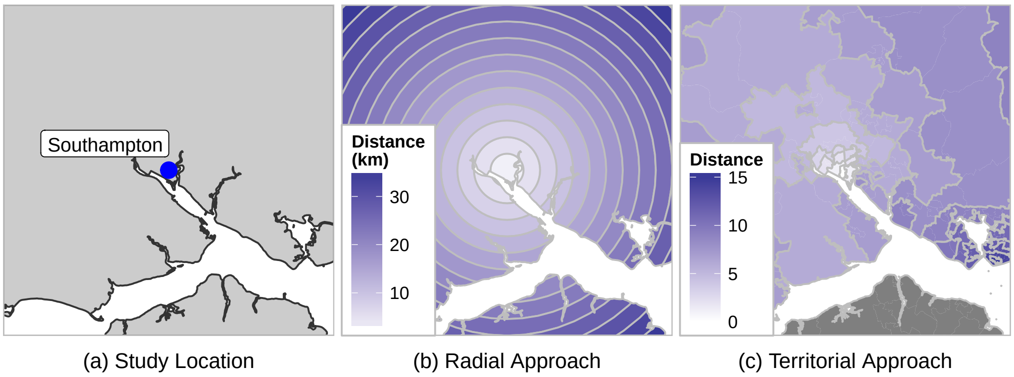


Figure 10.4: Two possible approaches for calculating distance within the ENSA methodology.

Determining Planning Scale

The model calculates the energy balance for each step in the city buffer rings/neighbouring regions. The aim of the model is to determine the scale at which energy demand can be met by renewable energy sources. If n represents the distance from the centre of location, the aim of the model is to satisfy the following equation:

$$\text{find } n \text{ where } \sum_{j=1}^{n} E_{Demand} - E_{Supply} = 0 \tag{10.1}$$

As the area of the assessment increases around a city, the demand may still increase if the study area includes other towns or cities. This can result in spikes in demand as the search radius increases, and is highlighted further within the case studies of this analysis.

Temporal Resolution

It is important to note that the model does not aim to achieve *energy autarkic* regions (i.e. regions which operate independently with no interconnection): it is not seen as desirable operating as a separate, local network, as the benefits of interconnection allow for electricity to be transferred between regions during periods of excess supply or demand within the network. As a result, the model focusses on an annualised temporal resolution with the assumption that interconnection is available to balance the daily and seasonal variation in supply and demand.

10.3 Application of Methodology

Having outlined the ENSA methodology within Section 10.2, this section highlights the use of the analysis within the UK context, applying the model to a number of case study regions. The analysis aims to highlight the challenge of spatial scale and quantify the challenges faced by cities to achieve greater energy self-sufficiency.

10.3.1 Energy Layers

The methodology outlined that energy neutrality covers all supply and demand technologies. However, this study focuses on the use of onshore wind as a case study technology, comparing the potential neutrality in relation to electricity demand. The two layers were therefore generated as follows:

- **Electricity Usage (Demand)**: electricity demand data was collected from aggregated statistics at the Middle Super Output Area (MSOA). This considers both domestic and commercial consumption, and provides annualised consumption values (DECC, 2014).
- **Onshore Wind Potential (Supply)**: the results for the onshore wind GIS-MCDA presented in Chapter 9 were used to estimate the onshore wind energy potential. Using the higher range estimate, it was assumed that within the initial analysis that all sites rated "Good" or "Excellent" could be developed. For potentially developable sites, the annual energy yields were derived using the average wind speed and Weibull transformations as outlined in Section 3.2, assuming the load profile of a typical 2MW wind turbine.

Study Locations

A number of case study towns and cities were selected for the energy scale modelling, as shown in Figure 10.5a. The population of each region is highlighted in Figure 10.5b to demonstrate the varying size of the regions selected. The cities and regions were selected to represent a mix of geographic locations and sizes. In addition, neighbouring urban areas in the Midlands (Coventry, Nuneaton & Rugby) were selected to highlight the potential resource conflict between cities and towns in the same region. This is explained further within Section 10.3.2.

It was decided that larger cities exceeding 1 million in population (London, Birmingham, Manchester etc.) would not be included within the analysis. Such large urban areas and surrounding conurbations are largely unsuitable for the development of onshore wind energy technologies as indicated within the results in Chapter 9, and therefore the results of this case study would provide limited use in determining the energy balance within these regions.

(a) Locational Map

Location	Longitude	Latitude	Population
Glasgow	−4.25	55.86	598,830
Bristol	−2.59	51.45	428,000
Coventry	−1.52	52.41	316,900
Plymouth	−4.14	50.38	256,384
Southampton	−1.40	50.91	236,900
Dumfries	−3.61	55.07	148,030
Rugby	−1.27	52.37	70,628
Nuneaton	−1.47	52.52	70,721
Lowestoft	1.75	52.48	58,560
Scarborough	−0.40	54.28	52,100
Inverness	−4.22	57.48	46,870
Aberystwyth	−4.08	52.42	13,040
Fraserburgh	−2.01	57.69	12,454
Wick	−3.09	58.44	6,954

(b) Site Details

Figure 10.5: UK cities and urban regions selected for analysis within the model.

Building Model

For each urban hub, the energy demand and potential supply were summarised in 1km radial buffers, up to a distance of 25km from the centre. Cumulative energy demand and supply figures were then calculated for each of these radial distances.

10.3.2 Results

A summary of the results for each study location is shown in Table 10.1. The table highlights the energy balance at 5km distances, up to a maximum of 25km. Within the table, the Energy Supply (S) and Demand (D) are shown, expressed as GWh/annum. These values are used to derive the energy balance, which indicates the percentage of energy demand which can be met from the renewable supply. Finally, the table highlights the distance in kilometres at which energy neutrality is achieved.

Table 10.1: Summary results table for the ENSA methodology, applied to 14 cities and towns within Great Britain.

	5km			10km			15km			20km			25km			
	S	D	B	S	D	B	S	D	B	S	D	B	S	D	B	Neutrality Distance (km)
Glasgow	26	8436	0	531	17080	3	2111	24691	9	13165	29755	44	29165	32850	89	
Bristol	12	6634	0	137	11675	1	480	13969	3	697	18247	4	1108	20624	5	
Coventry	21	4679	0	434	7377	6	2920	11660	25	4578	18947	24	6103	27539	22	
Plymouth	3	3322	0	3	4956	0	3	5531	0	211	6388	3	253	7278	3	
Southampton	0	4728	0	0	8687	0	0	11294	0	0	15072	0	0	19551	0	
Dumfries	12	844	1	151	1055	14	2777	1339	207	10627	1628	653	21799	2175	1002	14
Rugby	353	1433	25	1166	2130	55	2441	4649	52	3376	11310	30	4902	18294	27	
Nuneaton	673	1928	35	2657	5054	53	4370	10143	43	7078	16014	44	8647	27414	32	
Lowestoft	0	1119	0	0	1849	0	0	3247	0	0	4226	0	0	5085	0	
Scarborough	27	1197	2	45	1500	3	523	1845	28	1330	2202	60	2999	2741	109	24
Inverness	71	1427	5	1684	1756	96	2146	1985	108	3549	2448	145	7645	2944	260	11
Aberystwyth	84	357	24	241	447	54	1441	626	230	3927	856	459	8521	1130	754	12
Fraserburgh	1239	376	330	5443	511	1066	12163	638	1907	21295	877	2429	29967	1332	2250	4
Wick	1748	207	844	6258	229	2733	12302	277	4447	19990	338	5907	24926	399	6251	3

* S = Supply, D = Demand, B = Balance
† Both Supply and Demand are expressed as GWh/annum
‡ Balance expressed as a percentage

Spatial Scale Distance

To generalise the results of the model and compare study regions, the percentage of energy supply met by renewable sources can be plotted against distance, as shown in Figure 10.6. A value of 100% representing all demand is met by renewable energy supply (i.e. energy neutrality).

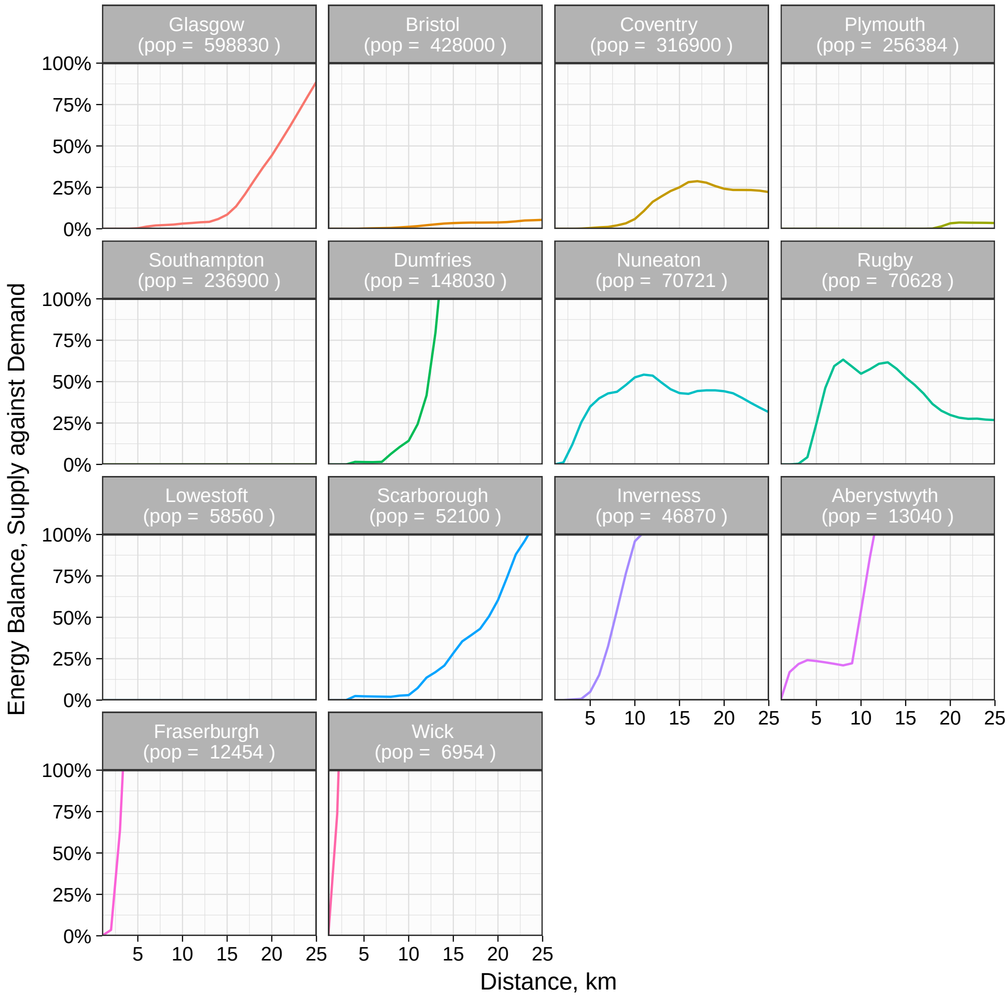


Figure 10.6: Graph highlighting the energy balance of the case study regions. 100% = energy neutrality. 0% = no renewable wind potential.

Figure 10.6 indicated that the population of the study region influences the ability of a region to achieve energy neutrality. Such a relationship would be expected, as lower population areas will generally experience a lower energy demand than a larger city. To further assess the relationship between energy neutrality and population, Figure 10.7 provides a scatterplot comparing the population against the distance at which energy neutrality was achieved. Of the locations considered, no area with a population greater than 150,000 was able to achieve energy neutrality within the study distance of 25km.

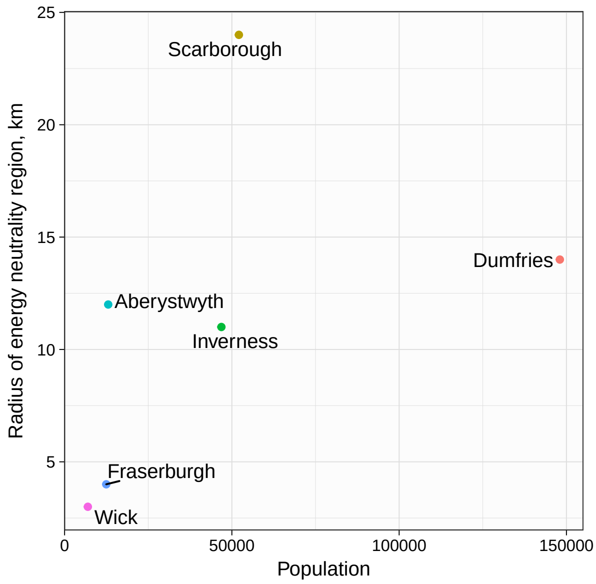


Figure 10.7: Graph comparing the distance at which energy neutrality is achieved compared to the population.

Neutrality Maps

Energy neutrality maps provide a way of visualising the spatial distribution of renewable energy demand, and identifying regions of high electricity consumption and potential regions for renewable energy development. Figure 10.8 provides an example of supply, demand, and energy neutrality maps for Scarborough, UK, to demonstrate the formation of the layers. Figure 10.9 provides the energy neutrality maps for each of the study areas considered within the model.

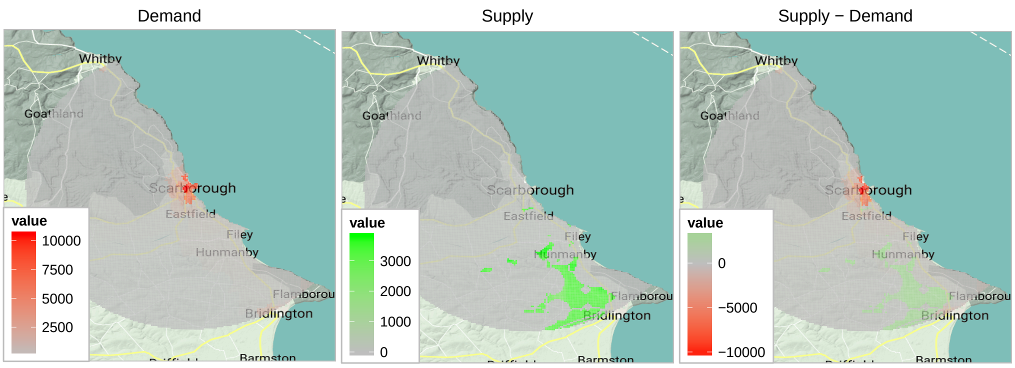


Figure 10.8: Energy Potential Mapping for Scarborough, UK.

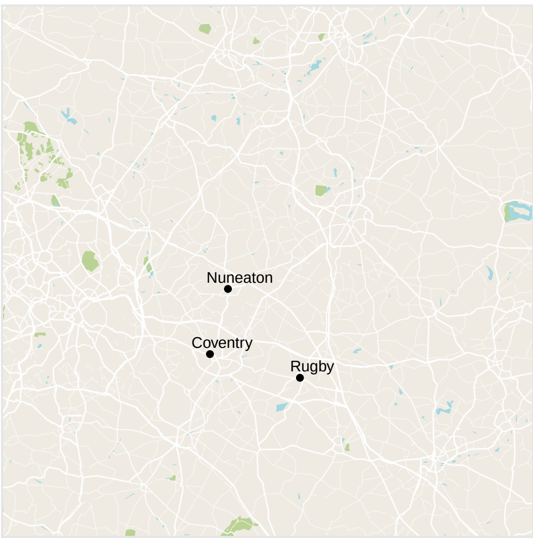
For the energy neutrality maps, several observations can be made:

- Both Wick and Fraserburgh are relatively small towns, with a large resource of wind energy in the surrounding hinterland. Within the 25km study distance, it is suggested that they are able to supply 62 and 22 times their electricity demand through onshore wind respectively.
- Inverness was the region with the highest energy demand to achieve energy neutrality.

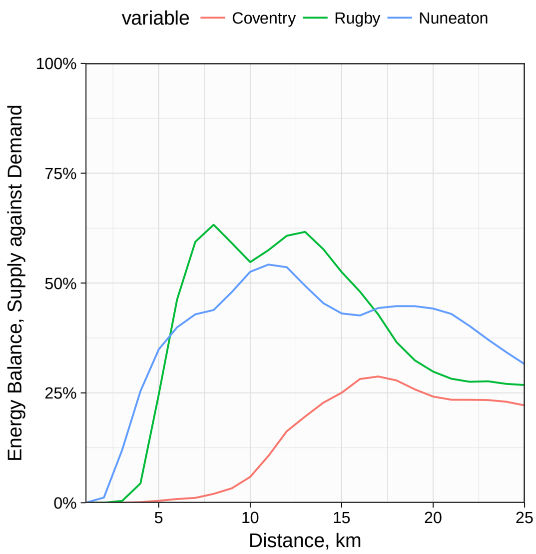
- Scarborough achieved energy neutrality at a distance of 24km. It can be seen that there are few renewable energy sites nearby the site, but a large area of wind energy suitability to the South East of the town.
- Whilst study areas generally experienced an increase in the net energy balance (Supply ÷ Demand), Coventry, Rugby and Nuneaton reduced with further distance. It can be seen in Figure 10.9c that this may be a result of the proximity of urban areas, with the study region including the outskirts of Birmingham.
- Both Southampton and Lowestoft were suggested to have no developable wind turbine locations within their surrounding study area.

Resource Conflict

It was highlighted within the methodology that the ENSA model only considers each urban hub individually. The spatial scale calculation does not consider whether the model overlaps other urban areas. As a result, it is possible for the energy demand of neighbouring cities to be included within the calculation as the size of the region increases. This effect was visible within the three case study urban areas of Coventry, Nuneaton and Rugby: as the regions were in close proximity, the increase in study buffer distance at each city resulted in the buffer zones encroaching into the neighbouring urban areas. This spatial proximity leads to a large increase in energy demand as the buffer area increases, which counters the more gradual demand increase found in more isolated areas.

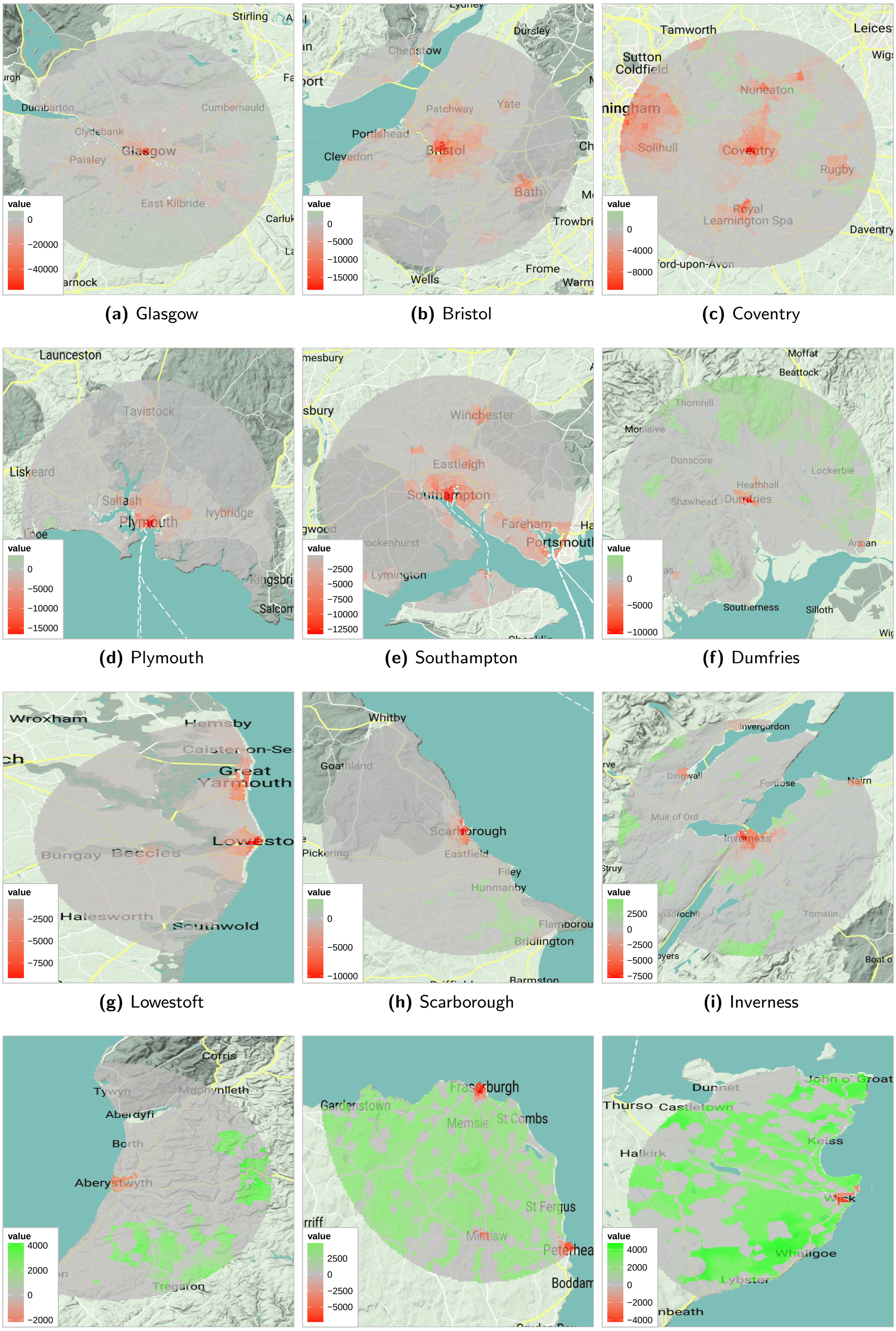


(a) Locations of competing energy cities.



(b) Energy self sufficiency curves.

Figure 10.10: Map and energy neutrality graph highlighting the potential resource conflict within the case study towns of Rugby, Nuneaton and Coventry.



(a) Glasgow **(b)** Bristol **(c)** Coventry

(d) Plymouth **(e)** Southampton **(f)** Dumfries

(g) Lowestoft **(h)** Scarborough **(i)** Inverness

(j) Aberystwyth **(k)** Fraserburgh **(l)** Wick

Figure 10.9: Energy neutrality maps for the case study locations. Maps display the annualised energy demand GWh per square kilometre.

10.4 Discussion

The buffer maps highlight the spatial dependency of renewable energy development opportunities. A number of cities were analysed which were comparable in size and population, including Southampton and Plymouth. However, both cities are highly restricted in their potential for onshore wind technologies, and therefore cannot achieve energy self-sufficiency within their surrounding hinterland. In comparison, Dumfries, with a population of 148000, was able to achieve energy neutrality at a distance of 14km.

The regional case study of Coventry, Nuneaton and Rugby highlights the potential resource conflict surrounding urban areas in close proximity. The results also demonstrate the issues of the optimal spatial planning at which towns may seek to plan their energy. Nuneaton and Rugby are both able to achieve a higher level of energy self-sufficiency when planning at a smaller scale: the results indicated an optimal distance of 12 and 8km respectively, where both towns were able to meet 50% of their energy demand. As the region increases in planning size, the potential energy balance decreases as the area contains Coventry and Birmingham, two larger urban areas with high energy demand.

Relating to existing literature, the study reinforced that the spatial scale of the energy planning is highly dependent on the population of the region. It was shown the regions of Samso, Denmark and Siena, Italy, had achieved energy neutrality within recent years (Casprini, 2013; Oudes & Stremke, 2018). However, these regions are comparatively small, with populations of 3,724 and 52,774 respectively, and therefore the achievement of this targets is seen as more achievable when compared to the larger city-regions considered within this analysis. As shown by the results, larger urban areas will face much greater difficulty in meeting energy demand, and therefore caution is required when using examples such as Siena and Samso as a blueprint when establishing ambitions for energy neutrality.

The results of this analysis should be taken within the context of the model, which only considered wind energy and electricity demand. Within the context of Great Britain, there are extensive opportunities to utilise solar photovoltaics, with large levels of development experienced within South England (DECC, 2016c). However, there is evidence that such resources can only provide a limited portion of urban energy demand, with estimates suggesting a maximum of 25% for medium-density urban areas like Southampton (Wu, 2017). The findings of this study therefore indicate the vulnerability that regions in the UK appear to face in meeting high energy demand within constrained areas. For the further use of this model, it is important that additional renewable energy technologies are integrated within the assessment.

10.5 Conclusion

It was demonstrated within the background literature in Section 2.2 and the literature review in Section 4.4 that there have been calls within literature for the consideration of spatial scale within the transition to renewable energy technologies (Bridge et al., 2013; Bulkeley & Betsill, 2005; Spath & Rohracher, 2012). Whilst there has been extensive modelling conducted to assess energy systems within the UK (Hall & Buckley, 2016), to the authors' knowledge, no studies have assessed the influence of spatial scale on energy planning. The work therefore aimed to explore the influence of spatial scale on the ability of a region to meet it's energy demand.

Within this Chapter, a generalised Energy Neutrality Scale Analysis (ENSA) methodology was developed to assess the potential for an urban region to achieve energy neutrality. The spatially explicit model assesses potential renewable energy generation against existing energy demand, with the aim to determine the scale at which the urban area can balance these two layers.

A case study was presented within this Chapter, using the ENSA methodology to compare the spatial scale at which onshore wind resources may meet the demand for urban electricity demand. This resource assessment of onshore wind built upon the analysis presented within Chapters 8 and Chapters 9 in an attempt to more accurately model the potential for onshore wind development. Within this case study, it was demonstrated that the ability for a urban area to achieve energy neutrality is highly spatially-dependent, and heavily influenced by the location of the urban conorbation. Cities in Scotland appear to have a easier task in achieving energy neutrality, whilst many regions in England appear to lack sufficient energy resources in the surrounding hinterland to meet the high levels of energy demand.

It was highlighted within the literature review in Section 4.4 that there has been widespread interest in the energy modelling within recent years (Hall & Buckley, 2016). The model aimed to provide a specific optimisation approach, but the outcomes from the approach should be integrated with generalised modelling. For example, LEAP and MARKAL/TIMES models are frequently used to consider long-term trends and the potential energy mixes within future scenarios. Such an approach would enable more advanced forecasting to be conducted and prioritise the key areas for investment.

Chapter Summary

- Energy Neutrality Scale Analysis (ENSA) methodology developed to assess the energy neutrality of a urban area and surrounding region
- 14 case study towns and cities were used to assess the scale at which energy neutrality could be achieved.
- Results indicate that the ability to achieve energy neutrality is highly spatially-dependent.

Chapter 11

Conclusion

The work in the thesis has presented three key research areas: firstly, statistical modelling was conducted to assess the likelihood of a wind energy project being accepted. Secondly, a geospatial decision support system was presented to identify suitable sites for wind energy development, building upon the previous statistical modelling. Finally, the spatial scale of energy planning was explored to assess its influence on the ability of a city or region to achieve energy neutrality. This chapter therefore aims to synthesize the three areas and highlight the key findings within the analysis, with the following objectives:

- to provide an overview of the thesis.
- to discuss the overall contributions of the research within the context of the existing literature.
- to highlight the implications of the research and potential practical applications.
- to explain potential limitations of the research.
- to make recommendations for future research areas.

11.1 Thesis Overview

Chapter 1 introduced the research challenge, and outlined the overall structure of the thesis. As explained within the objectives, the overall aim of the thesis was to was investigate the impact of spatial planning scale on the ability of a region to achieve energy neutrality, a term defined as "*the ability of a district to supply itself with sustainable energy generated within the boundaries of that district*" (Jablonska et al., 2011).

Chapter 2 outlined the broader context of renewable energy within the UK. The transition from the traditional large scale generation to smaller decentralised energy is challenging the existing structure of planning and development within the energy sector. As a result, there have been calls from cities and local authorities to be granted greater control and ownership of their energy planning. However, there has been limited questioning within this of whether this is the best spatial scale at which energy should be controlled (Bridge et al., 2013).

Whilst the primary aim of the thesis was to explore spatial scale, it was decided within Chapter 2 to narrow the scope to focus on a single renewable energy technology to allow for a more detailed assessment of a single renewable energy technology. Onshore wind was therefore selected to be studied in further detail for two primary reasons: firstly, there appeared to be a large gap between modelling and actual developments, with over 50% of projects rejected during planning (DECC, 2016c). Secondly, onshore wind represents a key opportunity for the UK, with high resource availability long being acknowledged (Strachan et al., 2006).

Chapter 3 expanded upon the issues framed within the background literature, and provided the relevant technical concepts surrounding the geospatial modelling of onshore wind energy.The traditional parameters used to locate wind energy projects were presented, including wind speed, distance to the powerlines and site access. Finally, it was shown that GIS-MCDA was the preferred technique used for site selection modelling, and that the Weighted Sum Method is most typically used within modelling to score the suitability of sites.

Chapter 4 reviewed the relevant academic literature for two key themes: onshore wind modelling and energy spatial scale. For onshore wind modelling, it was demonstrated that the existing methodologies fail to consider the social issues surrounding wind energy planning acceptance, and that there is limited justification of the weightings used for parameters within site selection modelling. Section 4.3 expanded upon the wide range of social parameters which are connected with planning acceptance, and identified many social parameters which were largely excluded within existing geospatial approaches, including social and demographic issues.

Chapter 5 built upon the limitations identified within the literature, and synthesised the overall research methodology of the thesis. The work was broadly split into two sections: firstly, data required collecting and processing into a suitable format. Secondly, the collected data could be used to explore the research questions developed from the literature review.

Chapter 6 detailed the process of collecting wind energy project information for the model. Concerns were raised surrounding the accuracy of the wind turbine data, and therefore the location of these sites were first validated. It was found that whilst errors were present, there was minimal error within the overall dataset, and therefore the positional accuracy was deemed suitable for further modelling.

Chapter 7 explained the collection and processing of contextual data, including technical, environmental and social parameters. This chapter built upon the literature review and attempted to collect parameters which were indicated to influence the suitability of wind energy site development (Langer et al., 2016). Parameters were aggregated for each wind energy site for use within the statistical analysis, and generalised rasters were also created to allow for a national model to be developed within the following chapters.

Chapter 8 presented statistical analysis which assessed the influence of wind energy site parameters on the planning acceptance of projects. The findings of this chapter revealed that local demographic and political parameters appear to influence the planning outcomes of projects, and that many of the geospatial parameters typically integrated into wind energy models appear insignificant in determining site approval. It was also shown that large areas of Great Britain appear to be highly unaccepting of wind energy projects, with projects having a low likelihood of acceptance within South England.

Chapter 9 built upon the findings of the statistical analysis, and developed a GIS-MCDA to determine suitable sites for development of onshore wind energy within Great Britain. The model integrated legislative, economic and site acceptability to increase the suitability of model results compared to existing approaches.

Chapter 10 demonstrated the development of a methodology to assess the renewable energy planning scale of cities. Using a case study of onshore wind energy, it was highlighted that the potential to achieve energy neutrality is dependent not only on the size of the region, but more importantly influenced by the spatial location of the area.

Chapter 11 provides the conclusions and future research of the thesis.

11.2 Research Objectives

As outlined in Chapter 1, the thesis investigated the impact of spatial planning scale on the ability of a region to achieve energy neutrality. Within this scope, the study also aimed to identify factors that may influence the planning acceptance of onshore wind energy projects, and to integrate this information into spatial modelling of onshore wind energy to identify suitable locations for development. To this effect, several objectives were identified, which are explained below:

1. **To understand and assess the influence of technical, demographic and political parameters on the acceptance of onshore wind projects within a UK context**.

Building upon a detailed literature review, a statistical model was developed to identify the key parameters which influence the planning success of onshore wind turbine energy projects. A total of 40 technical, geospatial, demographic and political variables were considered, and the results highlight that social and demographic parameters appear influential in the success of projects. This provides quantitative evidence to suppport existing literature, highlighting that traditional geospatial parameters (wind speed, proximity to national grid etc.) provide limited explanation for the spatial distribution of projects.

2. **To develop a predictive model of the planning application acceptance of onshore wind energy projects, based on the understanding achieved with the first objective**.

The results from the statistical analysis were generalised to form a spatial regression model to predict the likelihood of wind turbine projects being approved within the UK. The model assessed sites at a 500 metre resolution scoring the chance of planning acceptance from 0 to 100%. The results revealed that there are large areas within the UK which appear "*off-limits*" to development, most notably the South Coast of England.

3. **To assess the suitability of sites for onshore wind development, integrating the likelihood of the project receiving planning permission**.

Building upon the generalised statistical model, a GIS-MCDA model was developed to integrate economic, legislative and social constraints and identify potential sites for development of onshore wind energy. The integration of planning constraints into traditional modelling techniques highlighted the impacts of social constraint on onshore wind energy potential, reducing estimates from 200 GW to 16 GW.

4. **To assess the impact of spatial planning scale on the ability of a region to achieve energy neutrality, using onshore wind as a case study**.

A case-study of asessing the geospatial imbalance in energy supply and demand was conducted in 14 towns in the UK. The model compared onshore wind energy resources against electricity demand for each city, and determined the radial distance from each urban centre at which energy neutrality could be achieved.

5. **To develop a generalised approach for assessing the potential for energy neutrality of a region**.

A generalised ENSA methodology was developed, and the use of it was demonstrated within the fourth objective. The methodology is designed to be flexible, allowing additional renewable energy technologies (onshore wind, solar, hydro etc.) and energy demand (heating and transport). In addition, the methodology proposes both radial and territorial approaches to determine the scale at which energy neutrality can be acheived.

5. **To provide recommendations on the implication of the model results on regional energy planning**.

The results from the spatial scale analysis conducted call into question the rescaling of planning within the UK energy sector. Whilst some urban regions in the UK may feasibly be able to achieve energy neutrality, others appear highly resource constrained, and therefore transferring greater responsibility for the development of renewable energy resources may limit the potential for development.

11.3 Applications of Research

A large number of stakeholders are involved within the development of wind energy projects: from councils, developers and local populations. It is therefore important that information is available in a format which is easily accessible for all parties involved within the decision-making process. To this effect, an experimental dashboard was developed within the project to allow interaction with the model results, as shown in Figure 11.1. It is argued that such portals are crucial for increasing the understanding of geospatial research, as it allows users of all stakeholders an opportunity to query the model, and explore potential opportunities for development within their own region.

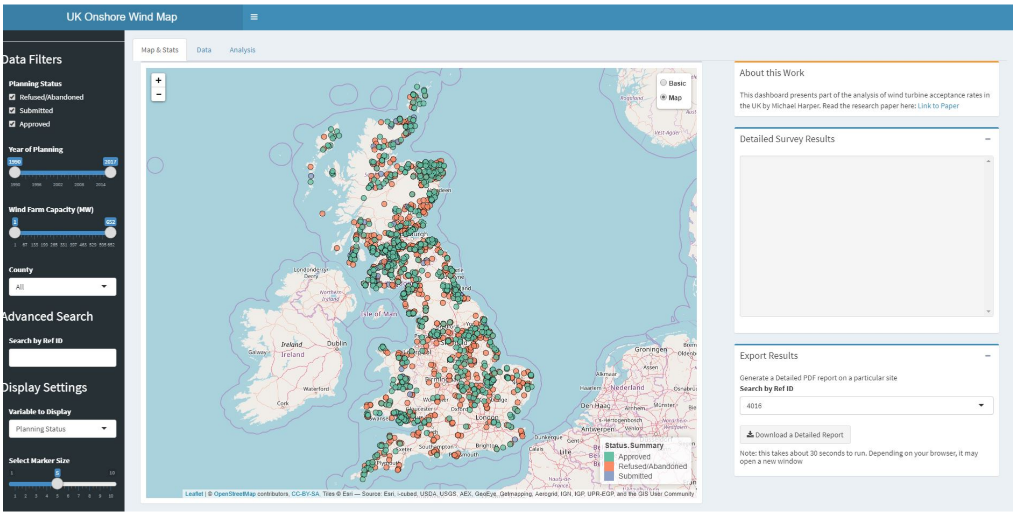


Figure 11.1: An experimental Wind Energy Database Dashboard, designed to query the results of the statistical model of onshore wind energy project acceptance rates. Available at: https://mikeyharper.shinyapps.io/windturbinemap/

From a national government perspective, it is of critical importance that the UK continues to develop renewable energy resources to meet emission reduction targets. Whilst onshore wind remains one of the cheapest forms of renewable energy technology, the difficulty in gaining planning permission has threatened the exploitation of the resource. By helping identify suitable sites, the GIS-MCDA analysis presented within this thesis can help determine feasible targets for onshore wind energy, and help reduce the cost of development of renewable energy technologies within the UK.

For a developer, the wind energy GIS-MCDA model developed here can provide a useful insight to where developments may want to be prioritised. The planning process of a wind energy is both long and expensive, with the estimated cost for a commercial wind energy planning process costing around £50000 to the developer, and applications frequently taking years to be approved (Renewables First, 2016). The model developed was found to have a predictive accuracy of 66% in predicting the likelihood of a project receiving planning approval. It is therefore important for developers that sites which are likely to be developed are selected, and even a marginal improvement in planning acceptance would be beneficial.

The results from the analysis also highlight that it is important that the developer does not overlook the broader social issues surrounding wind energy projects: the overall predictive model had a Pseudo R^2 of 0.2, and therefore geospatial parameters used in isolation only provide a limited influence in the planning outcome of a wind energy project. As previously stated, the findings provide evidence to support existing literature that geospatial tools in themselves are of limited applicability (Toke et al., 2008, Wolsink (2000), Warren & McFadyen (2010)). Developers should therefore ensure that projects engage local communities from a early stage, a model which is heavily applied within Germany whereby over 90% of wind energy projects are community-led (Cowell et al., 2017).

11.4 Limitations & Future Works

11.4.1 Wind Energy Statistical Modelling

It is recommended that future work integrates more detailed information about specific wind energy sites, specifically surrounding the planning and development process for sites. Literature suggests that geographic variables in themselves are insufficient to explain patterns of implementation of wind power (Toke et al., 2008), and there is strong evidence that the way in which the project is proposed influences the outcome. For example, community-led projects generally are more locally supported than those proposed by large developers or energy companies (Ellis & Ferraro, 2017). However, such inclusion would require the manual collection of data from each project, as a centralised record of such information does not exist to the author's knowledge.

Literature suggests that the acceptability of projects vary internationally (Langer et al., 2016). It is observed that Denmark and Germany have high levels of onshore wind energy development and generally greater acceptance rates of projects when compared to Great Britain (Fournis & Fortin, 2017; McLaren Loring, 2007). It is suggested that such differences have resulted from a difference in planning approaches, whereby Denmark and Germany have historically generated bottom-up mobilisation, whilst the UK has been a more complex combination of national contexts, major international actors, national public services and wind energy companies (Fournis & Fortin, 2017). An international comparison would enable a more detailed comparison of to be drawn between the two regions and help identify whether there are differences in development patterns in other countries.

The model developed within this study followed a logistic regression approach. It was discussed within Section 8.1 that linear relationships were assumed between the predictor variables and the logit. No transformations were made to the datasets, an approach generally recommended as it prevents distortion of the underlying dataset (Hosmer & Lemeshow, 2004). However, there were suggestions of slight non-linearity between the graphs: for example, proximity to both A and B roads may be non-linear: a wind turbine should not be too close to the road, as it can cause visual distraction to drivers, yet it cannot be too far away as access to site is required during the construction of the project. It is therefore suggested that non-linear relationships are explored within further analysis in order to better capture the relationship between parameters and the logit, ultimately resulting in an improved model fit.

There are opportunities to explore planning applications within more detail. Planning acceptance and rejection documents are available for all projects in the UK. To this effect, a research project conducted preliminary analysis of 50 projects to identify potential reasons for project rejection (Dimitriou, 2017). There are opportunities to expand this form of research, and it is proposed that key word analysis could be used to identify additional parameters for the development. As an example, it could be analysed how many times the planning documentation made reference to visual impacts or ecological concerns. Such an analysis would enable less structured data to be integrated within the model, with opportunities to gain further insight into the planning process.

11.4.2 Wind Energy GIS-MCDA

The model was built using more than 20 separate data sources, and therefore the model is highly influenced by the availability and quality of this underlying data. For example, the NOABL wind speed data is only available at 1km resolution and does not account for roughness of surface caused by urban developments of varying land cover such as forests (DTI, 2001). The errors from any dataset will have propagated through the analysis and, combined with errors from other layers, may cause inaccuracies in the output map. Sensitivity is recommended for further analysis to ensure more robust results, and has been used within existing GIS-MCDA to assess the variability of model results with changes in the input parameters (Neufville, 2013; Watson & Hudson, 2015).

Whilst the wind energy models aimed to integrate as many data sources as possible, there were difficulties in collecting some types of data. In particular, full ecological datasets could not be located to understand the impact of wind turbines may have on wildlife including birds and bats. Poorly located wind turbines can have adverse adverse impacts on birds and bats, and the impact on birds has been noted to be one of the main negative perceptions of wind turbines in general (Gove et al., 2016b). Some maps were available, but only covered aspects of Wales and Scotland (Bright et al., 2008; J. A. Brigth et al., 2009).

The modelling of wind energy is highly sensitive to external factors outside the control of planners and developers. This can be seen within the UK, whereby changes in laws within 2015 removed financial support for wind energy projects within Great Britain (Smith, 2016). Such a move effectively froze all further investment in onshore wind energy in the UK. However, there are signs that this policy change will be reversed, once again allowing for the development of onshore wind energy within parts of the UK. There is also uncertainty surrounding the implications of the UK leaving the European Union which may impact wind energy developments. Marsden (2017) notes that many protected areas are currently designated by the EU, and therefore there is uncertainty whether such areas will be "*off-limits*" in the future for developments of wind energy in the UK.

11.4.3 Spatial Scale Analysis

The analysis presented in this thesis represented a case study of onshore wind, and does not consider other renewable energy resources. Within the UK, there has been extensive development of solar photovoltaic, which passed 9GW of installed capacity in 2017. Such development has been largely driven by the fall in prices in solar panels experienced in recent years (DECC, 2016c). Research has demonstrated that building integrated solar may play an important contribution to city, however opportunities are limited by the energy density of solar photovoltaics (Wu, 2017)

There are opportunities to refine the scale analysis within the ENSA methodology. Within the existing radial approach, each energy balance analysis was conducted in isolation, and there is no consideration as to whether the areas are overlapping with the energy neutral zone of another region. This was highlighted within the Midlands case study of Nuneaton, Rugby and Coventry in Section 10.3.2, and resulted in several areas competing for the same resource. It is therefore recommended that future analysis seeks to resolve such resource conflict by preventing the overlap of neighbouring energy neutral areas.

The literature review highlighted that there has been extensive development of energy models. The work presented in this thesis does not intend to replace the existing models, but provide a specific function of understanding the optimal scale at which energy planning should be conducted. It is suggested that the resulting spatial scale calculated from the ENSA methodology is combined with existing energy models (LEAP, TIMES/MARKAL) to explore the impact that the spatial planning changes influence the renewable energy development.

Appendices & References

Appendix A

Statistical Analysis Primer

This Appendice provides background information for the statistical analysis conducted within the thesis.

A.1 Logistic Regression Overview

There are different types of regression analysis which use depends on the research objectives and variable format, with linear regression being one of the most frequently used methods. Linear regression analyses continuous outcomes, and assumes that the relationship between the outcome and independent variables follows a straight line. This can be applied in the case of multivariate linear regression, where the desire is to calculate the impact of multiple independent variables on the outcome. This can be expressed as:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_j X_j \tag{A.1}$$

where Y is the estimated continuous outcome, β_0 is the intercept, and X_j represents each independent variable weighted by is respective beta coefficient β_j. Despite its common usage, linear regression is not suitable where there is a binary outcome variable. Instead, logistic regression is usual method of choice (Stoltzfus, 2011). In essence, a logarithmic transformation is made to the outcome variable to define an outcome variable between 0 and 1, and can be expressed be expressed in a similar form to the linear regression formula:

$$\ln(\frac{Y_i}{1-Y_i}) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + b_3 X_3 + ... + b_j X_j \tag{A.2}$$

By rearranging equation A.2, it can be shown that:

$$\text{Probability of Outcome}(Y_i) = \frac{e^{\beta_1 X_1 + \beta_2 X_2 + b_3 X_3 + ... + b_j X_j}}{1 + e^{\beta_1 X_1 + \beta_2 X_2 + b_3 X_3 + ... + b_j X_j}} \tag{A.3}$$

where Y_i represents the estimated probability of being in one binary outcome category i versus the other, and $e^{\beta_1 X_1 + \beta_2 X_2 + b_3 X_3 + ... + b_j X_j}$ represents the linear regression equation for independent variables expressed in the logit scale, instead of the original linear format.

A.2 Independent Variables

To ensure that the logistic regression produces an accurate model, a number of critical factors must be taken into account during the formation of the analysis, as will be detailed in further in the following subsections. Logistic regression is flexible in the types of data type it will accept, including continuous, ordinal and categorical. Care should however be applied in selecting these variables. Variables should always be justified using well-established theory, past research, preliminary statistical analysis, or some sensible combination of these different options (Stoltzfus, 2011).

A second important consideration to be made is acknowledging and accounting for potential confounders, which can be described as variables whose relationship to both the outcome variable and another independent variable obscures the true association between that independent variable and the outcome (Anderson & Service), 1980). A commonly cited example is to suppose that there is a statistical relationship between ice cream sales and number of drownings in a given period. One could attempt to explain this causation by inferring a casual relationship (either that ice cream causes drowning, or that drowning causes ice cream consumption), however a more likely explanation is this relationship is spurious, and a third, confounding, variable (the season) influences the two variables. Confounding variables may not be as readily apparent as the given example, however it should be considered formally whether variables are being appropriately characterised and subsequently modelled. Path analysis diagrams can be particularly useful for this purpose.

A.3 Variable Selection

There has been a range of literature which suggests stepwise variable selection should be used to pre filter "insignificant" variables from a logistic model (Harrell, 2001). For example, Hosmer (2004) recommends that univariate analysis should be conducted for each variable to be considered for the model, and that any variable which has a p-value > 0.25 should be excluded from the analysis. However Harell (2001, p. 56) highlights that this creates a range of statistical issues, and recommends that problematic variables are only removed once they have been applied within the multivariate logistic model. Therefore, no prefiltering was used within the analysis conducted in this research.

A.4 Assumptions and Validation

In addition to these selection criteria for the variables, basic assumptions for conducting logistic regression must always be met. These include:

- **Independence of errors**: All sample group outcomes must be separate from each other (i.e. there are no duplicate responses). If the data contains repeated measures or other correlated outcomes, the errors will be similarly correlated and the assumption violated (Harrell, 2001).
- **Linearity of the logit for any independent variable**: It is assumed that there is a linear relationship between any continuous predictors and the logit of the outcome variable. A typical method of checking this assumption is to create a statistical term representing the interaction between each continuous variable and its natural logarithm. If these terms are statistically significant, the assumption is violated. Solutions include dummy coding the independent variable, or transforming it into a different scale, which will be discussed in greater detail later.
- **Absence of multicollinearity**: Multicollinearity (redundancy) among independent variables should be avoided. For example average wind speed and annual turbine electricity generation would both be highly correlated. A logistic model with collinear variables will usually result in large standard errors for the estimate beta coefficients of those variables. Collinearity can be tested by assessing the tolerance and variance inflation factor (VIF). The usual solution is to eliminate redundant variables.
- **Lack of influential outliers**: The independent variables must lack strongly influential outliers, whereby a predicted outcome may be vastly different from the actual outcome. If too many outliers are present, the overall accuracy of the model could be compromised. Outliers can be detected by looking at residuals (i.e. the difference between predicted and actual outcomes) and accompanying diagnostic statistics. A comparison can then be made for the overall model fit and beta coefficients with and without the outlier cases. It can then

be decided whether to retain outliers whose effect are not dramatic, or eliminate outliers with a particularly strong influence of the model.

Harrell (2001) argues that many of these assumptions are difficult to check without bias before the model is built, and recommends that checks and possible adjustments are only made once the model has been built. These will be explained further in Section A.8.

A.4.1 Number of Variables to Include

As part of selecting independent variables to be included within the model, it is important to decide an appropriate number. If too many independent variables are specified, it can result in an over-fit (and therefore unstable) model. Generally speaking, an over-fit model has higher-than-expected standard errors.

There are no set rules for the number of observations required. However, a typical rule of thumb is that there should be no fewer than 10 outcomes for each binary category (Harrell, 2001). For example, if 100 values were recorded, of which 60 were positive and 40 were negative, the logistic regression model could, at most, accommodate four independent variables.

A.5 Model Building Strategy

There are three model building strategies which can be used within logistic regression, each with a different emphasis and purpose: (1) *direct* (full, standard, or simultaneous) (2) *sequential* (hierarchical), or (3) *step-wise* (statistical). The use of these models is not necessarily interchangeable, and therefore care is required in identifying the suitable model to meet the research objectives.

The direct approach is often seen as the default approach, since all independent variables are entered into the model at the same time and no assumptions are made on the order or relative importance of those variables (Harrell, 2001). This is suitable if there are no specified hypotheses about which variables have greater importance than other variables.

The sequential/ hierarchical approach is applied by adding variables sequentially based on a predetermined order of priority. This is useful in situations where a hypothesis is being tested, and the variables perceived as the most important can be added first, and allows for a greater understanding of the fit of the model.

In contrast to the previous methods, the step-wise approach identifies independent variables which should be either added or removed from the model based on predefined statistical criteria that are influenced by the data being analysed (Harrell, 2001). There are a number of different methods, including forwarded selecting models (whereby variables are added one by one until no variable contributes significantly to the outcome) and backward elimination (all variables are entered simultaneously, and then those with a non-significant contribution are dropped one at a time until only statistically significant variables are left). Whilst this technique is regularly used within research, its use is somewhat controversial as it relies on automated variable selection that tends to take advantage of random chance factors within a given sample (Stoltzfus, 2011).

A.5.1 Internal and External Validation

There are a number of methods which can be used for validating the model. Internal validation confirms the model results within the same datasets, and the most common method being the holdout method, whereby the dataset is split into two separate subgroups called the training set and test set (Kohavi, 1995). The training group is used to create the logistic regression model, and the test group used to validate it.

An alternative method is to use k-fold cross validation, sometimes referred to as rotation estimation (Kohavi, 1995). The dataset D is randomly split in k mutually exclusive subsets (the folds) $D_1, D_2, D_3 ... D_k$ of approximately equal size. The model is trained and tested k, testing each against a model trained by the other subsets ($D \; D_t$). The cross validation estimate of accuracy is the overall number of correct classifications, divided by the number of instances in the dataset.

In addition to internal validation, efforts should be made to externally validate the dataset in a new study setting. If the results of either the internal or external validation raise any concerns (e.g. there is a poor fit in a particular area of the model), efforts should be made to make adjustment to the model as needed or to explicitally define any restrictions of the model use (Steyerberg et al., 2001).

A.6 Interpreting Model Fit

After the logistic regression has been created, the level of fit to the data must be assessed. The two most commonly used methods to assess model fit are the Pearson chi-squared and deviance statistics (Stoltzfus, 2011). Both of these measure the difference between the predicted and outcome variables, with a higher value suggesting greater difference and lack of a good fit of the model.

Deviance

The deviance statistic is based on summing the probabilities associated with the predicted and actual outcomes, and is an indicator of how much unexplained information there is after the model has been fitted. It is analogous to the residual sum of squares test used within multiple regression, and can be calculated as follows:

$$D = -2 \sum_{i=1}^{N} [Y_i \ln(P(Y_i)) + (1 - Y_i) \ln(1 - P(Y_i))] \tag{A.4}$$

where D is the Deviance, $P(Y_i)$ represents the probability of an event occuring for a given observation, and Y_i is the probability that Y occurs for the *i*th event.

The null deviance shows how well the response variable is predicted by a model that includes only the intercept (grand mean), while the residual deviance shows how well the response variable is predicted when including the independent variables in the model.

Pearson chi-squared

The Pearson chi squared χ^2 expresses the improvement of the model against the null model. It is calculated as:

$$\chi^2 = D_{null} - D_{new} \tag{A.5}$$

Pseudo R^2

R^2 are regularly used within linear regression to measure how well the model fits the data, however there is no direct equivalent term within logistic regression due to the logarithmic transformations. Instead, Pseudo-R^2 values are used which are analogous to the R^2 represented within linear regression, and represents the proportion of variance in the criterion that is explained by the predictors. There are a number of methods which can be used to calculate this:

1) *Hosmer and Lemeshow*, R^2_{HL} :

$$R_L{}^2 = \frac{D_{Model}}{D_{Baseline}} \tag{A.6}$$

2) *Cox and Snell* R^2_{CS} is based on the difference in deviance between the model and baseline, and the sample size n. It is expressed as:

$$R_{CS}{}^2 = \frac{D_{Model} - D_{Baseline}}{n} \tag{A.7}$$

3) *Nagelkerke* R_N^2: suggested the following amended for the value R_N^2

$$R_N{}^2 = \frac{R_{CS}{}^2}{1 - \exp\left(\frac{D_{Baseline}}{n}\right)} \tag{A.8}$$

Information Criteria

The Akaike Information Criterion (AIC) and Bayes Information Criterion (BIC) can be used to judge the model fit but penalises for the increased complexity which results from using a greater number of predictor variables. The intent of this variable is to prevent the inclusion of irrelevant predictors. The number itself is not meaningful, but is used to compare multiple models and help select the most suitable one. The AIC can be calculate as:

$$\text{AIC} = D + 2k \tag{A.9}$$

where D is the Deviance, k is the number of predictors used in the model. Alternatively the BIC can be used which adjusts the penalty by the number of cases, n, in the data:

$$\text{BIC} = D + 2k\log(n) \tag{A.10}$$

A.7 Interpreting Individual Variable Results

It is not only important to understand how the overall model fits but also to understand the influence of each parameter within the model. The methods used are explained in the following subsections.

Z-statistics

The z-statistic[1] can be used can be test whether the the β coefficient for the independent variable is significantly different from zero. If it is significantly greater than zero, it can be assumed that the predictor is making a significant contribution to the prediction of the outcome Y:

$$z = \frac{\beta}{SE_\beta} \tag{A.11}$$

where β is estimated regression coefficient, and SE_b is the standard error of β. However it is recommended that z-statistics should be used cautiously as when the regression coefficient is large, the standard errors can become inflated and results in the z-statistic being underestimated (Menard, 1995).

Odds Ratios

Results for independent variables are are usually presented as odds ratios (ORs). ORs reveal the strength of the independent variable's contribution to the outcome and are defined as the odds of the outcome occurring versus not occurring:

$$odds = \frac{p}{1-p} = \frac{Y}{1-Y} \tag{A.12}$$

95% Confidence Interval (CIs) are reported along with ORs as a measure of precision, and indicate whether the relationship is likely to hold for a large population). If the CI crosses 1.00, there may not be a significant difference in that population.

A.8 Model Refinement

The results for each model should be used carefully to ensure that the model provides an accurate fit to the data, and that assumptions are being met. These will be explained in greater detail below.

[1] alternatively referred to as the Wald statistic

Diagnostics

It is important that diagnostic statistics are checked before conclusions are reached about the adequacy of the final model. These diagnostic statistics help determine whether the overall model fit remains intact across all possible configurations of the independent variables.

Linearity of Logit

Once a variable has been identified as important, we can obtain the correct parametric relationship or scale in the model refinement stage. A number of methods are suggested for the identification and adjustment of any variables which may not be linear. While a number of methods are suggested by Menard [1995], univariate loess smoothed scatter plots are one of the most suitable methods.

Appendix B

Detailed Logistic Regression Results

This section provides the full outputs of the Hierarchical logistic regression analysis in addition to the results presented in Section 8.2.1.

B.1 Model 1: Physical attributes of the plant

This is based on some of the physical attributes of the wind turbines proposed. This includes the number of wind turbines of the site, and the turbine capacity which can be used to indicate the turbine size. The model initially included the overall wind farm capacity, however it was found that this was this was highly collinear with the number of turbines on the site. The capacity was therefore removed to reduce this influence on the model.

```
variables_model_1 <- c("No..of.Turbines", "Turbine.Capacity..MW.")
wind_models <- NULL
wind_models$No1 <- LogisticModel(variables_model_1, data_turbines)
(summary_model1 <- summary(wind_models$No1))  # Print Results
```

```
>
> Call:
> glm(formula = Formula, family = binomial(), data = Dataframe)
>
> Deviance Residuals:
>     Min       1Q   Median       3Q      Max
> -2.4157  -1.0931  -0.9783   1.2595   1.3548
>
> Coefficients:
>                        Estimate Std. Error z value Pr(>|z|)
> (Intercept)           -0.488147   0.112195  -4.351 1.36e-05 ***
> No..of.Turbines        0.017440   0.005004   3.485 0.000492 ***
> Turbine.Capacity..MW.  0.090942   0.052671   1.727 0.084240 .
> ---
> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
>
> (Dispersion parameter for binomial family taken to be 1)
>
>     Null deviance: 2323.1  on 1684  degrees of freedom
```

```
> Residual deviance: 2303.2  on 1682  degrees of freedom
>   (6 observations deleted due to missingness)
> AIC: 2309.2
>
> Number of Fisher Scoring iterations: 4
```

```r
# Check Diagnostics
LogisticDiagnostics(wind_models$No1)
```

```
> Chi Squared Test
> Chi Squared                19.861
> Df                         2
> Chi Squared p              0
>
> Pseudo R^2 for logistic regression
> Hosmer and Lemeshow R^2    0.009
> Cox and Snell R^2          0.012
> Nagelkerke R^2             0.016
>
> Variance Inflation Factors:
>       No..of.Turbines Turbine.Capacity..MW.
>              1.029437              1.029437
>
>  Checking for potential issues: No apparent issues with collinearity
>
> Durbin Watson Results:
>
>  lag Autocorrelation D-W Statistic p-value
>    1       0.1414363      1.715915       0
>  Alternative hypothesis: rho != 0
>
>  Is p-value greater than 0.05:             FALSE
>  Is DW ~ 2 (range of 0 to 4 acceptable):   TRUE
```

The Pseudo R^2 values highlight the relatively low level of the model. There are no issues with collinearity of the two variables or autocorrelation from the Durbin Watson Test.

```r
# Check Linearity of variables against logit
LogisticModelInt(variables_model_1, "Status.Summary", data_turbines)
```

```
> Statistically significant parameters from Logarithmic Transformations:
> No..of.Turbines
```

The logarithmic transformations are not statistically significant, which suggest that there are no issues with the linearity.

B.2 Model 2: Developer Parameters

The second model considers parameters which may be of interest to a developer, such as the site wind speed, proximity to powerlines and urban areas.

```r
# Add variables to parameter List
variables_model_2 <- ParameterUpdate(input = variables_model_1,
    add = c("WindSpeed45", "HVpowerline"))
wind_models$No2 <- LogisticModel(variables_model_2, data_turbines)
(summary_model2 <- summary(wind_models$No2))
```

```
>
> Call:
> glm(formula = Formula, family = binomial(), data = Dataframe)
>
> Deviance Residuals:
>     Min       1Q   Median       3Q      Max
> -2.2810  -1.0862  -0.9791   1.2578   1.4194
>
> Coefficients:
>                       Estimate Std. Error z value Pr(>|z|)
> (Intercept)          -1.049153   0.351584  -2.984  0.00284 **
> No..of.Turbines       0.015591   0.005017   3.108  0.00189 **
> Turbine.Capacity..MW.  0.105459   0.053104   1.986  0.04704 *
> WindSpeed45           0.068092   0.045589   1.494  0.13527
> HVpowerline           0.009160   0.006193   1.479  0.13910
> ---
> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
>
> (Dispersion parameter for binomial family taken to be 1)
>
>     Null deviance: 2323.1  on 1684  degrees of freedom
> Residual deviance: 2297.6  on 1680  degrees of freedom
>   (6 observations deleted due to missingness)
> AIC: 2307.6
>
> Number of Fisher Scoring iterations: 4

> Chi Squared Test
> Chi Squared              25.458
> Df                       4
> Chi Squared p            0
>
> Pseudo R^2 for logistic regression
> Hosmer and Lemeshow R^2   0.011
> Cox and Snell R^2         0.015
> Nagelkerke R^2            0.02
>
> Variance Inflation Factors:
>       No..of.Turbines Turbine.Capacity..MW.           WindSpeed45
>              1.064218              1.043055              1.082025
>           HVpowerline
>              1.053137
>
>  Checking for potential issues: No apparent issues with collinearity
>
> Durbin Watson Results:
```

```
>
>  lag Autocorrelation D-W Statistic p-value
>    1       0.1410696      1.716657       0
>  Alternative hypothesis: rho != 0
>
>  Is p-value greater than 0.05:             FALSE
>  Is DW ~ 2 (range of 0 to 4 acceptable):   TRUE
```

```
# Linearity of variables against logit
LogisticModelInt(variables_model_2, "Status.Summary", data_turbines)
```

```
> Statistically significant parameters from Logarithmic Transformations:
> No..of.Turbines, HVpowerline, HVpowerline_Int
```

Results suggest that HV Powerlines should be checked as they are not linear.

There is a relatively limited improvement in this model compared to the first model. Proximity to powerlines is seen as a significant parameter, however there appear to be issues with its linearity to the logit.

B.3 Model 3: Year of Application

```
variables_model_3 <- ParameterUpdate(variables_model_2, add = c("year"))
wind_models$No3 <- LogisticModel(variables_model_3, data_turbines)
(summary_model3 <- summary(wind_models$No3))
```

```
>
> Call:
> glm(formula = Formula, family = binomial(), data = Dataframe)
>
> Deviance Residuals:
>     Min       1Q   Median       3Q      Max
> -1.9946  -1.0641  -0.7951   1.1798   1.8858
>
> Coefficients:
>                        Estimate Std. Error z value Pr(>|z|)
> (Intercept)          220.563775  24.774173   8.903  < 2e-16 ***
> No..of.Turbines        0.006626   0.004926   1.345    0.179
> Turbine.Capacity..MW.  0.378137   0.063037   5.999 1.99e-09 ***
> WindSpeed45            0.062650   0.046812   1.338    0.181
> HVpowerline            0.009557   0.006482   1.474    0.140
> year                  -0.110540   0.012359  -8.944  < 2e-16 ***
> ---
> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
>
> (Dispersion parameter for binomial family taken to be 1)
>
>     Null deviance: 2323.1  on 1684  degrees of freedom
> Residual deviance: 2211.4  on 1679  degrees of freedom
>   (6 observations deleted due to missingness)
```

```
> AIC: 2223.4
>
> Number of Fisher Scoring iterations: 4
```

B.4 Model 4: Proximity to Features

This model builds upon the previous models to include the full list of geospatial parameters derived in the previous analysis. These provide the proximity to the nearest features and include landscape and environmental designations.

```
variables_model_4 <- ParameterUpdate(variables_model_3, add = c("Airports_Trans",
    "ARoads_Trans", "BRoads_Trans", "MinRoads_Trans", "Motorways_Trans",
    "Railway_Trans", "UrbanRegions_Trans", "AONB_Trans", "NationalParks_Trans",
    "HCoast_Trans", "NNR_Trans", "RAMSAR_Trans", "SACS_Trans",
    "SPA_Trans", "SSSI_Trans", "MilitarySites_Trans"))
wind_models$No4 <- LogisticModel(variables_model_4, data_turbines)
(summary_model4 <- summary(wind_models$No4))
```

```
>
> Call:
> glm(formula = Formula, family = binomial(), data = Dataframe)
>
> Deviance Residuals:
>     Min       1Q   Median       3Q      Max
> -1.8953  -1.0405  -0.7084   1.1121   2.2594
>
> Coefficients:
>                         Estimate Std. Error z value Pr(>|z|)
> (Intercept)           250.081969  26.084355   9.587  < 2e-16 ***
> No..of.Turbines         0.001785   0.005389   0.331   0.7405
> Turbine.Capacity..MW.   0.368250   0.065059   5.660 1.51e-08 ***
> WindSpeed45            -0.066284   0.056618  -1.171   0.2417
> HVpowerline             0.009930   0.007464   1.330   0.1834
> year                   -0.125272   0.013026  -9.617  < 2e-16 ***
> Airports_Trans          0.012051   0.007742   1.557   0.1196
> ARoads_Trans           -0.002949   0.011973  -0.246   0.8054
> BRoads_Trans           -0.028077   0.017709  -1.585   0.1129
> MinRoads_Trans          0.062959   0.067681   0.930   0.3523
> Motorways_Trans        -0.007598   0.005878  -1.293   0.1961
> Railway_Trans           0.008606   0.008418   1.022   0.3066
> UrbanRegions_Trans      0.094292   0.060859   1.549   0.1213
> AONB_Trans              0.024390   0.005840   4.176 2.96e-05 ***
> NationalParks_Trans     0.031548   0.006386   4.940 7.82e-07 ***
> HCoast_Trans           -0.014977   0.008332  -1.797   0.0723 .
> NNR_Trans              -0.003165   0.006882  -0.460   0.6456
> RAMSAR_Trans            0.013511   0.006512   2.075   0.0380 *
> SACS_Trans             -0.005652   0.009224  -0.613   0.5400
> SPA_Trans              -0.018309   0.007899  -2.318   0.0205 *
> SSSI_Trans              0.024218   0.024448   0.991   0.3219
> MilitarySites_Trans    -0.001295   0.007498  -0.173   0.8629
> ---
```

```
> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
>
> (Dispersion parameter for binomial family taken to be 1)
>
>     Null deviance: 2323.1  on 1684  degrees of freedom
> Residual deviance: 2139.7  on 1663  degrees of freedom
>   (6 observations deleted due to missingness)
> AIC: 2183.7
>
> Number of Fisher Scoring iterations: 4
```

Check to see whether regression model adequately represents the data.

```
> Chi Squared Test
> Chi Squared              183.38
> Df                       21
> Chi Squared p            0
>
> Pseudo R^2 for logistic regression
> Hosmer and Lemeshow R^2   0.079
> Cox and Snell R^2         0.103
> Nagelkerke R^2            0.138
>
> Variance Inflation Factors:
>      No..of.Turbines Turbine.Capacity..MW.          WindSpeed45
>             1.293795             1.426528             1.513980
>           HVpowerline                 year        Airports_Trans
>             1.301395             1.427341             1.816467
>          ARoads_Trans         BRoads_Trans        MinRoads_Trans
>             1.376831             1.250865             1.896046
>      Motorways_Trans        Railway_Trans    UrbanRegions_Trans
>             1.553907             1.697850             2.136182
>           AONB_Trans   NationalParks_Trans          HCoast_Trans
>             1.316817             1.321069             1.370836
>            NNR_Trans          RAMSAR_Trans            SACS_Trans
>             1.402576             1.695932             1.494591
>            SPA_Trans            SSSI_Trans   MilitarySites_Trans
>             1.765613             1.165950             1.723045
>
>  Checking for potential issues: No apparent issues with collinearity
>
> Durbin Watson Results:
>
>  lag Autocorrelation D-W Statistic p-value
>    1       0.1231317      1.752378       0
>  Alternative hypothesis: rho != 0
>
>  Is p-value greater than 0.05:            FALSE
>  Is DW ~ 2 (range of 0 to 4 acceptable):   TRUE

> Statistically significant parameters from Logarithmic Transformations:
> No..of.Turbines, SPA_Trans, No..of.Turbines_Int
```

Areas of Outstanding Natural Beauty (AONB), National Parks and SPAs are statistically significant environmental and landscape designations. However it appears that there may be issues with AoNB linearity.

B.5 Model 5: Census Variables

This model adds Census data to understand whether demographic variables can be linked to the turbines. Qualifications, Age, Social Grade and Tenure were added to the model.

```
>
> Call:
> glm(formula = Formula, family = binomial(), data = Dataframe)
>
> Deviance Residuals:
>     Min       1Q   Median       3Q      Max
> -2.1351  -1.0248  -0.6687   1.0901   2.1888
>
> Coefficients:
>                        Estimate Std. Error z value Pr(>|z|)
> (Intercept)           2.496e+02  2.648e+01   9.424  < 2e-16 ***
> No..of.Turbines       1.893e-03  5.498e-03   0.344  0.73058
> Turbine.Capacity..MW.  3.538e-01  6.572e-02   5.383 7.32e-08 ***
> WindSpeed45          -5.684e-02  5.891e-02  -0.965  0.33461
> HVpowerline           1.051e-02  7.518e-03   1.398  0.16216
> year                 -1.237e-01  1.320e-02  -9.377  < 2e-16 ***
> Airports_Trans        1.132e-02  7.974e-03   1.420  0.15562
> ARoads_Trans          2.258e-04  1.215e-02   0.019  0.98518
> BRoads_Trans         -2.380e-02  1.800e-02  -1.322  0.18610
> MinRoads_Trans        5.640e-02  6.858e-02   0.822  0.41089
> Motorways_Trans      -5.662e-03  6.048e-03  -0.936  0.34916
> Railway_Trans         1.445e-02  8.628e-03   1.675  0.09394 .
> UrbanRegions_Trans    1.315e-01  6.185e-02   2.126  0.03349 *
> AONB_Trans            1.743e-02  6.050e-03   2.881  0.00396 **
> NationalParks_Trans   2.701e-02  6.630e-03   4.074 4.62e-05 ***
> HCoast_Trans         -1.148e-02  8.547e-03  -1.343  0.17937
> NNR_Trans            -2.356e-03  6.993e-03  -0.337  0.73614
> RAMSAR_Trans          1.255e-02  6.611e-03   1.899  0.05758 .
> SACS_Trans           -3.136e-04  9.384e-03  -0.033  0.97334
> SPA_Trans            -1.787e-02  8.012e-03  -2.231  0.02570 *
> SSSI_Trans            2.571e-02  2.474e-02   1.039  0.29871
> MilitarySites_Trans  -7.672e-04  7.601e-03  -0.101  0.91960
> QualPercL4           -3.301e-02  6.726e-03  -4.908 9.19e-07 ***
> AgeMean              -4.296e-02  1.691e-02  -2.541  0.01105 *
> TenureOwned           1.817e-04  3.643e-04   0.499  0.61806
> ---
> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
>
> (Dispersion parameter for binomial family taken to be 1)
>
>     Null deviance: 2323.1  on 1684  degrees of freedom
> Residual deviance: 2108.0  on 1660  degrees of freedom
>   (6 observations deleted due to missingness)
```

```
> AIC: 2158
>
> Number of Fisher Scoring iterations: 4
```

Check to see whether regression model adequately represents the data.

```
# Diagnostics
LogisticDiagnostics(wind_models$No5)
```

```
> Chi Squared Test
> Chi Squared               215.057
> Df                        24
> Chi Squared p             0
>
> Pseudo R^2 for logistic regression
> Hosmer and Lemeshow R^2   0.093
> Cox and Snell R^2         0.12
> Nagelkerke R^2            0.16
>
> Variance Inflation Factors:
>       No..of.Turbines Turbine.Capacity..MW.           WindSpeed45
>              1.305828              1.430732              1.608825
>            HVpowerline                  year        Airports_Trans
>              1.314353              1.439489              1.891999
>           ARoads_Trans          BRoads_Trans        MinRoads_Trans
>              1.391384              1.273828              1.909885
>       Motorways_Trans         Railway_Trans    UrbanRegions_Trans
>              1.610107              1.759852              2.165507
>             AONB_Trans   NationalParks_Trans           HCoast_Trans
>              1.386636              1.393019              1.421512
>              NNR_Trans           RAMSAR_Trans            SACS_Trans
>              1.417735              1.714050              1.508830
>              SPA_Trans             SSSI_Trans    MilitarySites_Trans
>              1.785564              1.167404              1.738657
>             QualPercL4               AgeMean           TenureOwned
>              1.130358              1.322023              1.574151
>
>  Checking for potential issues: No apparent issues with collinearity
>
> Durbin Watson Results:
>
>  lag Autocorrelation D-W Statistic p-value
>    1       0.1171062      1.764259       0
>  Alternative hypothesis: rho != 0
>
>  Is p-value greater than 0.05:             FALSE
>  Is DW ~ 2 (range of 0 to 4 acceptable):   TRUE

> Statistically significant parameters from Logarithmic Transformations:
> No..of.Turbines, HCoast_Trans, SPA_Trans, No..of.Turbines_Int, HCoast_Trans_Int
```

Conclusions:

- Increased levels of qualification appear to reduce the likelihood of acceptance
- Age_Median and Mean are highlight collinear. Median value removed

B.6 Model 6: Political Parameters

This adds information from local authority composition. Represents the complete model presented within the report.

```
variables_model_6 <- ParameterUpdate(variables_model_5, add = c("Con_share",
    "Lab_share", "LD_share"))
# Could add 'SNP_PC_sha'
wind_models$No6 <- LogisticModel(variables_model_6, data_turbines)
(summary_model6 <- summary(wind_models$No6))
```

```
>
> Call:
> glm(formula = Formula, family = binomial(), data = Dataframe)
>
> Deviance Residuals:
>     Min       1Q   Median       3Q      Max
> -2.1882  -1.0201  -0.6702   1.0944   2.1904
>
> Coefficients:
>                         Estimate Std. Error z value Pr(>|z|)
> (Intercept)            2.418e+02  2.732e+01   8.849  < 2e-16 ***
> No..of.Turbines        1.711e-03  5.512e-03   0.310  0.75620
> Turbine.Capacity..MW.  3.543e-01  6.587e-02   5.379 7.49e-08 ***
> WindSpeed45           -7.840e-02  6.173e-02  -1.270  0.20410
> HVpowerline            1.151e-02  7.739e-03   1.487  0.13701
> year                  -1.200e-01  1.357e-02  -8.840  < 2e-16 ***
> Airports_Trans         1.008e-02  8.196e-03   1.230  0.21851
> ARoads_Trans           9.562e-05  1.217e-02   0.008  0.99373
> BRoads_Trans          -2.279e-02  1.800e-02  -1.266  0.20555
> MinRoads_Trans         5.437e-02  6.882e-02   0.790  0.42956
> Motorways_Trans       -1.966e-03  6.879e-03  -0.286  0.77502
> Railway_Trans          1.464e-02  8.727e-03   1.678  0.09334 .
> UrbanRegions_Trans     1.354e-01  6.220e-02   2.177  0.02949 *
> AONB_Trans             1.700e-02  6.094e-03   2.789  0.00528 **
> NationalParks_Trans    2.909e-02  6.779e-03   4.292 1.77e-05 ***
> HCoast_Trans          -8.784e-03  9.083e-03  -0.967  0.33351
> NNR_Trans             -2.100e-03  7.024e-03  -0.299  0.76498
> RAMSAR_Trans           1.143e-02  6.657e-03   1.717  0.08594 .
> SACS_Trans             1.449e-04  9.462e-03   0.015  0.98778
> SPA_Trans             -1.707e-02  8.081e-03  -2.112  0.03466 *
> SSSI_Trans             2.919e-02  2.489e-02   1.173  0.24085
> MilitarySites_Trans   -5.758e-04  7.758e-03  -0.074  0.94084
> QualPercL4            -3.156e-02  6.992e-03  -4.513 6.38e-06 ***
> AgeMean               -4.074e-02  1.699e-02  -2.397  0.01652 *
> TenureOwned            2.762e-04  3.722e-04   0.742  0.45803
> Con_share             -1.938e-03  3.195e-03  -0.607  0.54409
> Lab_share              3.404e-03  3.766e-03   0.904  0.36608
```

```
> LD_share               2.544e-03  4.873e-03   0.522  0.60172
> ---
> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
>
> (Dispersion parameter for binomial family taken to be 1)
>
>     Null deviance: 2323.1  on 1684  degrees of freedom
> Residual deviance: 2105.4  on 1657  degrees of freedom
>   (6 observations deleted due to missingness)
> AIC: 2161.4
>
> Number of Fisher Scoring iterations: 4
```

```
# Diagnostics
LogisticDiagnostics(wind_models$No6)
```

```
> Chi Squared Test
> Chi Squared                217.681
> Df                         27
> Chi Squared p              0
>
> Pseudo R^2 for logistic regression
> Hosmer and Lemeshow R^2   0.094
> Cox and Snell R^2          0.121
> Nagelkerke R^2             0.162
>
> Variance Inflation Factors:
>       No..of.Turbines Turbine.Capacity..MW.           WindSpeed45
>              1.318151              1.434903              1.766284
>           HVpowerline                  year         Airports_Trans
>              1.398842              1.525445              1.994051
>          ARoads_Trans          BRoads_Trans        MinRoads_Trans
>              1.398824              1.277994              1.918567
>       Motorways_Trans         Railway_Trans    UrbanRegions_Trans
>              2.075823              1.801724              2.183934
>            AONB_Trans   NationalParks_Trans           HCoast_Trans
>              1.400399              1.451549              1.590689
>             NNR_Trans          RAMSAR_Trans            SACS_Trans
>              1.427297              1.733981              1.526815
>             SPA_Trans            SSSI_Trans    MilitarySites_Trans
>              1.808605              1.178912              1.807902
>            QualPercL4               AgeMean           TenureOwned
>              1.223422              1.336942              1.644344
>             Con_share             Lab_share              LD_share
>              2.324242              2.911172              1.887431
>
>  Checking for potential issues: No apparent issues with collinearity
>
> Durbin Watson Results:
>
>  lag Autocorrelation D-W Statistic p-value
>    1       0.1189905      1.760569       0
```

```
>  Alternative hypothesis: rho != 0
>
>  Is p-value greater than 0.05:            FALSE
>  Is DW ~ 2 (range of 0 to 4 acceptable):   TRUE
```

B.7 Model 7: Cumulative Development

This includes parameters which indicate how site the planning permission was to other sites at the time of the application.

```
variables_model_7 <- ParameterUpdate(variables_model_6, add = c("NearestTurbineBuilt",
    "NearestTurbineRejected", "UrbanLarge"), remove = "UrbanRegions")
wind_models$No7 <- LogisticModel(variables_model_7, data_turbines)
(summary_model7 <- summary(wind_models$No7))
```

```
>
> Call:
> glm(formula = Formula, family = binomial(), data = Dataframe)
>
> Deviance Residuals:
>     Min       1Q   Median       3Q      Max
> -2.3836  -1.0030  -0.6349   1.0628   2.3263
>
> Coefficients:
>                          Estimate Std. Error z value Pr(>|z|)
> (Intercept)             2.341e+02  2.785e+01   8.406  < 2e-16 ***
> No..of.Turbines         1.336e-03  5.591e-03   0.239 0.811165
> Turbine.Capacity..MW.   3.457e-01  6.668e-02   5.184 2.17e-07 ***
> WindSpeed45            -8.951e-02  6.263e-02  -1.429 0.152967
> HVpowerline             1.131e-02  8.065e-03   1.402 0.160816
> year                   -1.161e-01  1.383e-02  -8.394  < 2e-16 ***
> Airports_Trans          8.367e-03  8.294e-03   1.009 0.313104
> ARoads_Trans            4.050e-04  1.247e-02   0.032 0.974087
> BRoads_Trans           -2.173e-02  1.892e-02  -1.148 0.250970
> MinRoads_Trans          6.003e-02  7.004e-02   0.857 0.391379
> Motorways_Trans        -1.969e-03  6.971e-03  -0.282 0.777561
> Railway_Trans           1.475e-02  8.891e-03   1.659 0.097054 .
> UrbanRegions_Trans      1.431e-01  6.420e-02   2.228 0.025857 *
> AONB_Trans              1.695e-02  6.169e-03   2.748 0.006005 **
> NationalParks_Trans     2.920e-02  6.871e-03   4.249 2.15e-05 ***
> HCoast_Trans           -9.303e-03  9.203e-03  -1.011 0.312060
> NNR_Trans              -2.467e-03  7.092e-03  -0.348 0.727976
> RAMSAR_Trans            1.232e-02  6.753e-03   1.824 0.068128 .
> SACS_Trans              1.010e-03  9.631e-03   0.105 0.916468
> SPA_Trans              -1.782e-02  8.210e-03  -2.171 0.029963 *
> SSSI_Trans              3.111e-02  2.520e-02   1.235 0.216943
> MilitarySites_Trans     1.189e-03  7.913e-03   0.150 0.880606
> QualPercL4             -3.135e-02  7.079e-03  -4.428 9.52e-06 ***
> AgeMean                -4.122e-02  1.736e-02  -2.375 0.017570 *
> TenureOwned             1.815e-04  3.782e-04   0.480 0.631179
```

```
> Con_share              -2.517e-03  3.249e-03  -0.775 0.438532
> Lab_share               2.610e-03  3.802e-03   0.687 0.492303
> LD_share                9.439e-04  4.956e-03   0.190 0.848960
> NearestTurbineBuilt    -1.544e-02  4.102e-03  -3.765 0.000167 ***
> NearestTurbineRejected  1.888e-02  3.290e-03   5.738 9.60e-09 ***
> UrbanLarge             -6.025e-03  1.299e-02  -0.464 0.642836
> ---
> Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
>
> (Dispersion parameter for binomial family taken to be 1)
>
>     Null deviance: 2323.1  on 1684  degrees of freedom
> Residual deviance: 2069.2  on 1654  degrees of freedom
>   (6 observations deleted due to missingness)
> AIC: 2131.2
>
> Number of Fisher Scoring iterations: 4
```

Check to see whether regression model adequately represents the data.

```
# Diagnostics
LogisticDiagnostics(wind_models$No7)
```

```
> Chi Squared Test
> Chi Squared               253.84
> Df                        30
> Chi Squared p             0
>
> Pseudo R^2 for logistic regression
> Hosmer and Lemeshow R^2   0.109
> Cox and Snell R^2         0.14
> Nagelkerke R^2            0.187
>
> Variance Inflation Factors:
>        No..of.Turbines  Turbine.Capacity..MW.            WindSpeed45
>               1.317263               1.442330               1.789681
>            HVpowerline                   year         Airports_Trans
>               1.493487               1.556441               1.999623
>           ARoads_Trans           BRoads_Trans         MinRoads_Trans
>               1.421234               1.373694               1.936020
>        Motorways_Trans          Railway_Trans    UrbanRegions_Trans
>               2.096251               1.832006               2.279739
>             AONB_Trans    NationalParks_Trans           HCoast_Trans
>               1.406804               1.451301               1.596139
>              NNR_Trans           RAMSAR_Trans             SACS_Trans
>               1.427238               1.742869               1.537200
>              SPA_Trans             SSSI_Trans     MilitarySites_Trans
>               1.827295               1.187218               1.836968
>             QualPercL4                AgeMean            TenureOwned
>               1.235065               1.358887               1.665323
>              Con_share              Lab_share               LD_share
>               2.343596               2.912146               1.902670
```

```
>    NearestTurbineBuilt NearestTurbineRejected            UrbanLarge
>               1.447754               1.446266              2.158412
>
>  Checking for potential issues: No apparent issues with collinearity
>
> Durbin Watson Results:
>
>  lag Autocorrelation D-W Statistic p-value
>    1       0.1139821      1.770515       0
>  Alternative hypothesis: rho != 0
>
>  Is p-value greater than 0.05:            FALSE
>  Is DW ~ 2 (range of 0 to 4 acceptable):   TRUE

> Statistically significant parameters from Logarithmic Transformations:
> AgeMean, NearestTurbineBuilt, AgeMean_Int, NearestTurbineBuilt_Int
```

Appendix C

Conference Papers

Two conference papers were presented as part of the PhD research work:

- **Identifying key influences for planning acceptance of onshore wind turbines**: presented in 30th International Conference on Efficiency, Cost, Optimisation, Simulation and Environmental Impact of Energy Systems, San Diego, July 2017. This is based on the analysis presented in Chapter 8.
- **Identifying suitable locations for onshore wind turbines using a GIS-MCDA approach**: presented at 16th International Conference on Sustainable Energy Technologies, Bologna, July 2017. The paper is based around the content of Chapter 9.

Identifying key influences for planning acceptance of onshore wind turbines

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Abstract:

There is a global drive to develop renewable energy power generation to reduce environmental impacts and enhance energy security especially through indigenous resources. Wind energy conversion both on and offshore is one of the most effective technologies to provide sustainable power. In the deployments of such technologies, geographical information systems are extensively used to identify suitable sites for the installation of wind turbines. However, there are concerns that such approaches fail to model site suitability accurately, and in particular fail to account for the difficulties faced in gaining planning permission. This study has explored whether the planning success of proposed wind turbine projects can be predicted using a range of geospatial parameters based on Great Britain as a case study. Logistic regression is used to assess the relationship between appropriate variables and planning outcome. The results indicate that the size of the project, percentage of the local population with high levels of qualifications, the average age, and local political composition emerge as key influences affecting planning approval. To the authors' knowledge, this is the first study which has quantitatively linked regional social and political data to the planning outcome of wind turbines. These findings can help reduce the level of planning issues encountered for proposed wind turbine, improving the accuracy of GIS modelling of wind turbines.

Keywords:

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

1. Introduction

Increased environmental concern and issues surrounding security of supply have led to a global drive to develop renewable energy systems. In the European Union, over $40 billion is invested annually in renewable energy technologies (mostly wind and solar) and it is expected to increase by a further 50% by 2020 [1].

Onshore wind power generation is now competitive with fossil energy in many countries and is one of the most mature renewable energy technologies available. However, there are major technical challenges in identifying suitable sites for wind turbine farms. Projects often face strong local opposition, as can be seen from the low acceptance rates of wind turbines in Great Britain, with over 50% of onshore projects rejected [2].

A large number of geospatial models have been produced to determine site suitability for wind farms [3–19], but such models are highly sensitive to the underlying modelling assumptions, and there has been limited validation of these models against actual developments patterns. A few studies have aimed to rigorously quantify key influences on historical planning outcomes [20–23], but such analysis has yet to be integrated within a full geospatial model.

The overall objective of the programme of work to which this paper contributes is to build an overarching model integrating resource availability and likely acceptability of onshore wind turbine projects. This paper presents the first stage of this analysis, assessing which parameters influence wind turbine planning outcomes utilising a range of physical, geographical, demographic and political parameters. In doing so, it responds to calls to merge qualitative and quantitative analysis of wind projects to gain a greater understanding of project approval [24].

The work presented here has four parts: a review of existing literature relevant to onshore wind modelling; collection and processing of appropriate data sources used within the analysis; research methodology and results and finally discussion of the theoretical and practical implications of the research and further research opportunities.

2. Background

Geographic Information Systems (GIS) are tools designed to capture, store, manipulate, analyse, manage, and present spatial or geographic data [25]. They are used extensively to assist in locating wind farms, and combine a range of geospatial information into the decision-making of wind energy development [26]. Early work by Voivontas et al. [3] and Baban and Parry [4] provide examples of such analysis, and established the structure for an international range of studies [9–19] which have largely followed the approach outlined in Fig. 1.

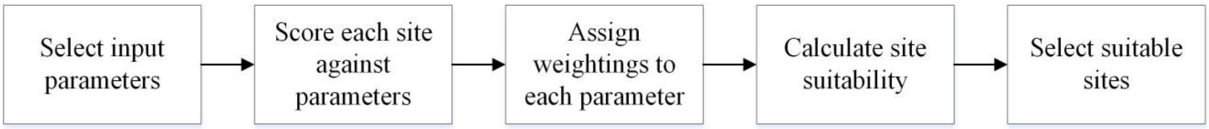

Fig. 1. Typical stages of geospatial models for assessing wind turbine site suitability

Similar parameters are used throughout the studies, and ideal sites are typically identified as having high average wind speeds; not being close to urban areas; not in protected landscapes (e.g. National Parks); not close to airports (to minimise radar interference); close to roads for access and finally close to power lines for grid connection. However the weights for each parameter in subsequent predictive models have traditionally been determined using surveys and questionnaires [4, 7, 13, 18] or previous literature [14, 15, 17]. To the authors' knowledge, there have been no attempts to statistically validate the relative importance of parameters used and it is therefore unclear whether the parameters currently used are actually appropriate for site approval rates. In a significant contribution, this paper derives these weights using a statistically rigorous methodology and then tests their ability to correctly predict planning outcomes.

In addition, there is increased awareness of the wider social challenges surrounding the development since geographical variables in themselves are insufficient to explain patterns of implementation of wind power [27, 28]. Recent studies have explored how planning decisions were influenced by key actors (e.g. local communities, planning authorities, project developers) [20, 21] and local characteristics [29]. In particular, a study by Van Rensburg et al. [23] explored wind farms project planning approval against a range of technological and institutional process variables. The results suggested a number of variables appeared significant for planning including the proximity to Natura 2000 sites (an EU protected habitat designation); sites with high bird sensitivity; hub height and project installed capacity. In addition, the study noted that proximity of the nearest dwellings and wind speeds appeared insignificant, a finding which counters the views reported within many previous studies. Other work has investigated the social factors that may influence planning decisions [24, 30–34]. For example, studies within Great Britain suggest that support for wind developments decreases as both income and age increase [31], and people with higher levels of qualifications are less likely to support projects [32]. However, whilst these potential social factors have been identified, there have been no attempts to include these parameters within geospatial analysis of potential turbine developments. This work therefore integrates the demographic and political parameters into geospatial analysis with the aim of improving the validity of such a model.

In consequence this paper builds upon many of the concepts developed by Van Rensburg et al., but aims to apply these concepts to a broader range of geospatial, demographic and political datasets.

3. Data and Variables

An extensive literature review was conducted to identify geospatial and social parameters which have been connected to the planning outcomes of wind turbine applications. Parameters were collated from existing geospatial models, and reviewing qualitative and quantitative studies. The key sources included Baban and Parry [4], Langer et al. [24] and European Wind Energy Association [35].

3.1. Study Region

The study was conducted across Great Britain (England, Scotland & Wales). This was chosen because of the broadly similar categorisation of land types, nature designation, data availability and legislation across these regions.

3.2. Data Sources

Information for turbine planning applications was collected through the Renewable Energy Planning Database (REPD) [36] with planning dates between January 1991 and December 2016 (n=1755). 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 two variables: accepted and rejected. Fig. 2 highlights the location of the sites the distribution of these points and the planning status.

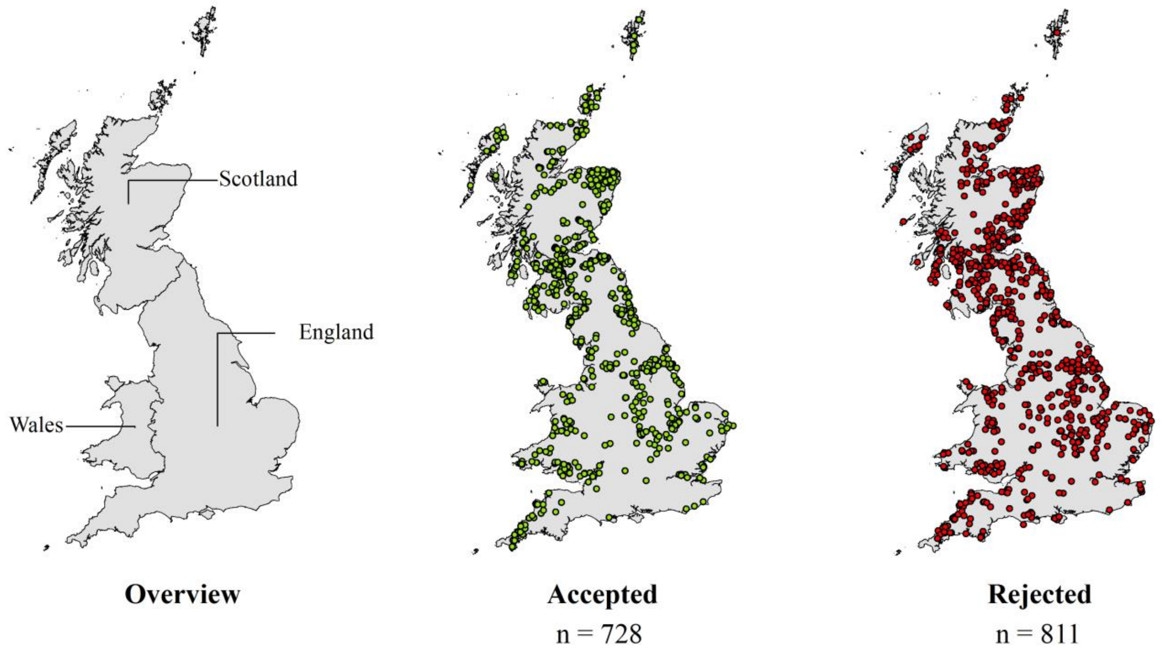

Fig. 2. Location of onshore wind turbine planning applications used within the study. Location data extracted from the Renewable Energy Planning Database.

Wind speeds were taken from the Numerical Objective Analysis of Boundary Layer (NOABL) wind speed database, which provides estimated annualised wind speed at 45m elevation at a resolution of 1km grid [37]. This source is used extensively by wind assessment studies conducted within the UK [4, 10, 17].

Physical features including roads, railways and urban areas were collected from OS Strategi [38]. The electricity transmission network and Airport location data (civil and military) were extracted from Open Street Maps (OSM) [39].

Site elevation and slope is used by a number of studies to determine site suitability [4, 9]. Elevation was extracted from a Digital Elevation Model (DEM) of Europe at a 25m resolution [40]. This data was then used to calculate the slope using the slope calculation tool within ArcGIS 10.2.

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. Data was collected for mean age; social grade (percentage of higher social class AB, representing higher & intermediate managerial, administrative, professional occupations); tenure (ownership of homes) and levels of qualifications (percentage of population with university degree).

Planning decisions for turbines are influenced by the Local Planning Authority, which are the local political bodies within the UK [41]. In total, there are 405 local authorities across England, Scotland and Wales. Data was collected for the Conservatives; Labour, Liberal Democrat and the Scottish National Party (SNP), which between them hold 95% of seats within Great Britain.

3.3. Data Transformations

The data sources came in a range of formats including points, lines and polygons (roads, urban regions etc.), tabular (census and political data) and rasters (wind speed, elevation, slope) as highlighted in Fig. 3. These parameters had to be summarised for each wind turbine farms within the model. ArcGIS 10.3 was used to aggregate the datasets as follows:

- **Points, lines and polygons:** A spatial join was completed to find the distance to the nearest feature for each turbine. A value of 0 is given if the turbine is within the feature.
- **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 tool "Raster Value to Point" was used to extract the values for each site.

The complete list of parameters used within the analysis is shown in Appendix A.

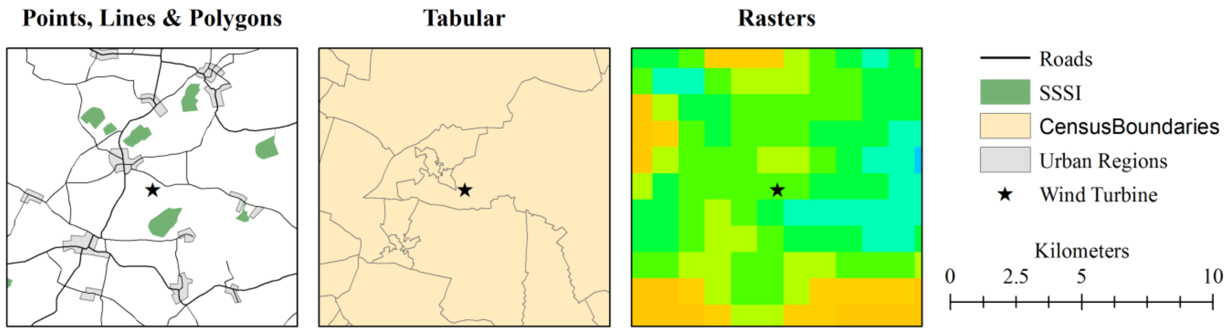

Fig. 3. Mapping of Parameter data to turbine locations

4. Methodology

A 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 2. A hierarchical approach was applied to the model building by adding variables sequentially based on the following order of priority: Physical attributes of the site; Distance to Features; Environmental and Natural Designations; Social (Census) Data and finally Political Data. This order was selected to reflect the current approach of geospatial studies, which as mentioned above, generally do not consider the last two.

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 [42]. 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 [43].

Once all parameters had been included within the model, a parsimonious model (one that accomplishes a desired level of explanation or prediction with as few predictor variables as possible) was produced to remove uninfluential parameters [44]. The Akaike Information Criterion (AIC) was used to determine the best fitting subset of parameters. This method avoids the issues associated with step-wise approaches of parameter removal [42] and resulted in nine effective parameters.

In addition, 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) [45] as well as differing institutional support, with Scotland in particular placing a greater emphasis on the development of onshore wind [46]. To test this, separate logistic regression models were produced for each country. These re-used the subset of influential nine parameters (see Fig. 4) with the additional inclusion of *Wind Speed*, which had been suggested to be influential in previous research [23].

5. Results

Table 1 provides the results from the parsimonious logistic regression analysis associating planning approval for all available cases. Statistically significant positive trends (e.g. increase in the parameter increases success rates) were observed for Number of Turbine; Distance to Urban Regions; Distance to National Parks; Percentage of local council Liberal Democrat and Percentage of local council Labour. Negative associations were found for Qualifications above L4 (university degree); Mean Age and Distance to Natura 2000 sites. The odds ratios (OR) are shown for each parameter in Fig. 4, 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.

As noted, the reduced parameter set of parameters were also used to assess models for England, Scotland and Wales separately and the odds ratios for each parameter for these models are shown in Fig. 5.

Finally, a summary of the different logistic models is shown in Table 2.

Table 1 Logistic Regression results for the AIC optimised model.

Variable	Estimate	Std. Error	Pr	Sig.	Odds Ratio	Odds Ratio C.I.	
						2.5%	97.5%
(Intercept)	1.675	0.755	0.027	*	5.337	1.22	23.596
Number of Turbines	0.017	0.007	0.01	**	1.018	1.005	1.032
Distance to Urban Region	0.158	0.051	0.002	**	1.171	1.06	1.295
Distance to National Park	0.008	0.002	0	***	1.008	1.005	1.011
Distance to Ramsar	0.007	0.004	0.089	.	1.007	0.999	1.014
Distance to SPA	-0.013	0.006	0.041	*	0.987	0.974	0.999
Qualifications, L4	-0.036	0.007	0	***	0.965	0.952	0.978
Mean Age	-0.043	0.016	0.006	**	0.958	0.928	0.988
Political, Labour Share	0.009	0.003	0.001	***	1.009	1.004	1.015
Political, Liberal Democrat	0.009	0.004	0.03	*	1.009	1.001	1.017

*Significance Codes '***' 0.1%, '**' 1%, '*' 5% '.' 10%*

Table 2 A summary of the logistic regression models

	Full	Reduced	Nested		
			England	Scotland	Wales
Observations	1476	1476	646	698	132
Parameters	27	9	10	11	10
Nagelkirke R^2	0.11	0.10	0.11	0.16	0.24
Pearson Chi-squared	113.7	111.9	51.5	89.3	25.9
Residual deviance	1932	1932	833	895	157
Model Accuracy	60%	62%	60%	65%	57%

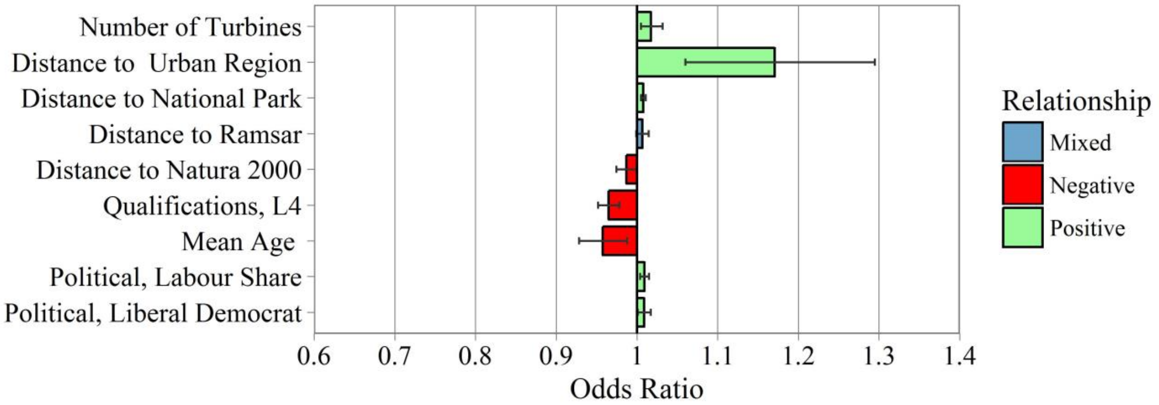

Fig. 4. Odds plot for the reduced logistic regression mode. Error bars show the 95% confidence interval.

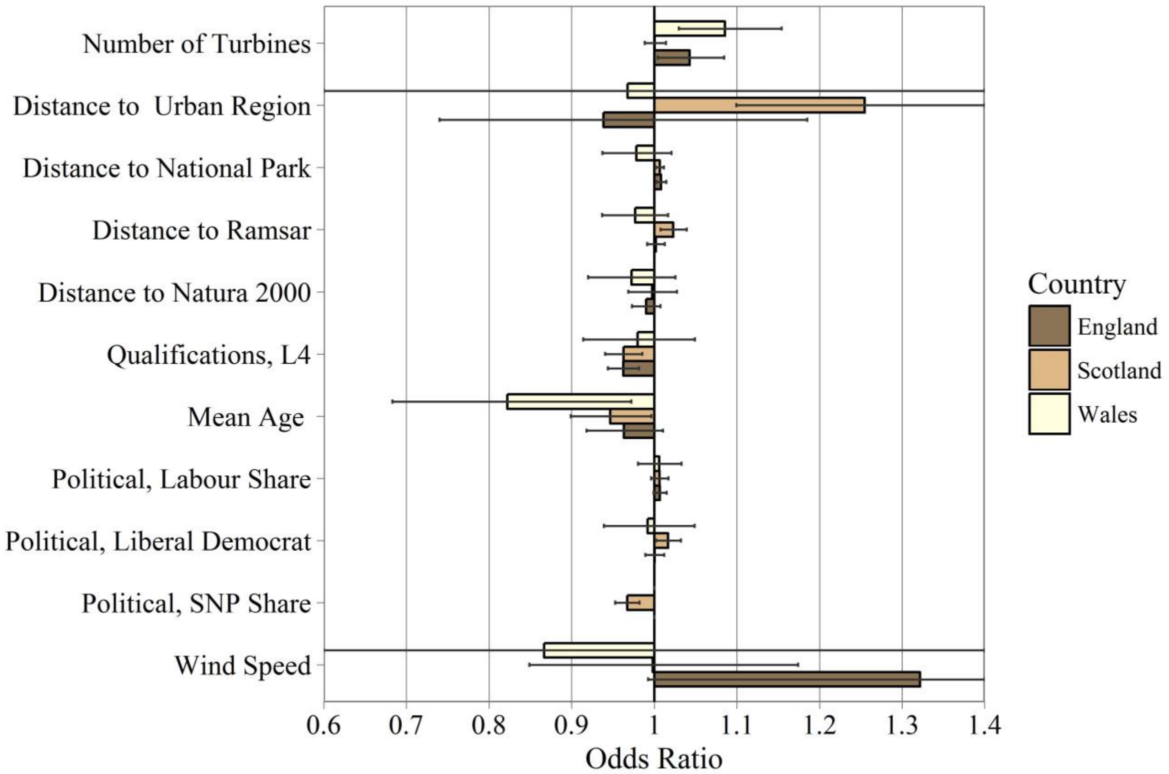

Fig. 5. Odds plot for the nested logistic regression models for England, Scotland and Wales. Error bars indicate 95% confidence intervals.

6. Discussion

The ‘all countries’ model highlighted several key parameters, as shown in Fig. 4. First, for project characteristics, the number of turbines appears significant in determining project success although the magnitude of the effect is relatively small. It is suggested that developers are more likely to appeal the decisions made against larger wind farms, as rejection of such projects would result in a large loss of revenue.

A number of physical parameters have been identified as significant. The distance to urban areas has been highlighted as an indicator, although with considerable uncertainty as the confidence intervals indicate. 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 local population, with project in closer proximity to urban areas being more likely to be rejected. However, there are conflicting views in literature whether NIMBY views impact wind turbines, with a range of positive [21, 47] and negative [23, 28, 29] studies.

For Landscape and environmental designations, distance to National Parks and Natura 2000 sites were indicated as significant, although have marginal impacts. It had been expected that such parameters would be more influential, as the visual impact of wind turbine land is often stated as a reason for project refusal [48].

Both 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 [22] that developers were "keen to avoid relatively privileged communities and target areas where people are thought to less likely put up a fight".

For political variables, the percentage of local council authority control for Liberal Democrats and Labour both appear significant. It is suggested that this may be because these parties are broadly supportive of wind projects at a national level, and as such, local planning decisions may be more favourable for proposed projects. In addition, other studies have highlighted that voters of these parties are personally more in favour of onshore wind [49], which may result in less local objection against projects in areas where they have stronger support.

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

Fig. 5 highlights that, as hypothesised, the odds ratios for parameters vary by country, although the reduced number of cases in each model increases the uncertainty substantially as indicated by the confidence intervals. It can be seen that parameters such as Turbine Capacity; Wind Speed and Distance to Urban Regions show differing relationships for each country. These suggest that there may be differing motives for projects within each country as well as differential planning constraints. For example, projects within England appear to place higher emphasis on wind speed. It should be noted that the wind resource is more marginal in England, and it is suggested that low wind speed may be an easy way for projects to be rejected.

For the Scotland model, the percentage of local council authority control for SNP appears significant, with increased percentage resulting in a lower acceptance rate. However, upon further inspection, this was deemed to be a potential confounding variable with the year of application: SNP have increased their share of council seats between 1990 and 2016 from 15% to 35%, while at the same time the average acceptance rates have reduced from around 75% to 40% across that period. This parameter therefore appears to capture a national trend, rather than highlighting any local political influences.

As shown in Table 3, there is a relatively low level of fit with Psuedo R^2 values of 0.1. Splitting the model into England, Scotland and Wales marginally improved these values to 0.11, 0.16 and 0.24, suggesting the model was a better fit for Scotland and Wales. However, while the accuracy of the Scotland model improved against the 'all countries' model (60% to 65%), the Wales only model has decreased to 57%, suggesting that this model has been overfitted due to the reduced number of observations (n = 132).

7. Conclusions & Implications

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 and political 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.

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 [48], 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 turbine sites. These findings provide evidence to support existing literature that GIS tools in themselves are of limited applicability [20, 25], 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) [27, 50, 51].

Because of the low model fit, future work aims to integrate more detailed information about specific wind turbine sites. It has not been possible to include detailed information of the project development within the analysis. Studies have highlighted that the interaction of developers with local communities are key indicators of positive planning approval outcomes [20, 52–54].

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.

Acknowledgments

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Supplementary Files

The supporting data and analysis is available on Southampton Eprints (http://eprints.soton.ac.uk/) and through GitHub (https://github.com/mikey-harper/WindStatisticalAnalysis)

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Table A.1: 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 [2]	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 [37]	Raster	Annualised Wind Speed	Continuous	m/s
7	Features	Airports	OpenGeo [55]	Points	Distance to Feature	Continuous	km
8		Roads *	OS Strategi [38]	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 **		Lines	Distance to Feature	Continuous	km
12	Landscape	Areas of Outstanding Natural Beauty	National Heritage England [56]	Polygons	Distance to Feature	Continuous	km
13		National Parks		Polygons	Distance to Feature	Continuous	km
14		Heritage Coast		Polygons	Distance to Feature	Continuous	km
15	Nature	Special Protection Areas		Polygons	Distance to Feature	Continuous	km
16		National Nature Reserve		Polygons	Distance to Feature	Continuous	km
17		Sites of Special Scientific Interest		Polygons	Distance to Feature	Continuous	km
18		Special Areas of Conservation		Polygons	Distance to Feature	Continuous	km
19	Geographic	Elevation	EU DEM [40]	Raster	Height above sea level	Integer	m
20		Slope	Derived from 18	Raster	Gradient	Continuous	%
21	Census	Level of Qualification	ONS [57]	Tabular	Higher than L4 ***	Continuous	%
22		Age		Tabular	Mean	Continuous	Years
23		Social Grade		Tabular	Social Grade AB ****	Continuous	%
24		Tenure		Tabular	Home Ownership	Continuous	%
25	Political	Conservatives	[58]	Tabular	Percentage of Council	Continuous	%
26		Labour		Tabular	Percentage of Council	Continuous	%
27		Liberal Democrat		Tabular	Percentage of Council	Continuous	%

** Roads are broken into four main categories: Motorways, A Roads, B Roads and Minor Roads. ** High Voltage network at 140-400kV. *** L4 represents degree level or above. **** AB represents Higher & intermediate managerial, administrative, professional occupation*

Identifying suitable locations for onshore wind turbines using a GIS-MCDA approach

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Onshore wind generation is one of the most cost-effective methods of renewable electricity generation. However, there is often difficulty in identifying suitable sites for development. To assist such systems, geospatial information systems are extensively used in identifying suitable sites for wind turbines: these models predominantly focus on the technical and legislative constraints, and have a limited understanding of the social issues surrounding development. As a result, there are concerns with the validity of these models in accurately determining suitable sites and fail to acknowledge the strong local opposition which some projects can experience. Building upon previous statistical analysis, this paper presents a geospatial multi-criteria decision analysis that integrates the technological, legislative, and social constraints to determine suitable sites for onshore wind turbine development. To the authors' knowledge, this is the first study that aims to understand whether suitable sites are likely to receive planning permission and to integrate this into the decision-making process. The findings highlight the importance of considering the planning constraints within modelling and demonstrates the limitations in identifying suitable sites for development.

Keywords: Onshore Wind, GIS, MCDA

1. INTRODUCTION

Increased environmental concern and issues surrounding security of supply have led to a global drive to develop renewable energy systems. This has led to a large increase in the development of these technologies, which has resulted in significant interest in identifying suitable locations for these to be installed.

While onshore wind power generation is now both a mature technology and competitive with traditional energy supplies in many countries, there are difficulties in identifying suitable sites for wind turbine farms. To assist this development, many geospatial models have been proposed. However, there are concerns that current models provide limited actionable guidance, and in particular fail to account for the challenges faced in projects obtaining planning permission. This can be highlighted in the United Kingdom, where more than 50% of wind turbine projects in the United Kingdom are rejected at planning (DECC, 2016), suggesting that wind turbines are being proposed in areas which are socially unsuitable for development.

The overall objective of the programme of work, to which this paper contributes, is to build a predictive model for locating onshore wind turbine projects, integrating resource availability and the likelihood of a project receiving planning acceptance. In the first stage, statistical analysis was conducted to identify the key influences for planning acceptance of onshore wind turbines. This paper presents the second stage of the analysis, outlining the geospatial model developed for assessing site suitability and decision making for identifying suitable sites for wind turbine development.

The work presented here has four parts: an overview of the literature relevant to onshore wind GIS modelling; a description of the research methodology; presentation of the model results and finally discussion of the theoretical and practical implications of the research and further research opportunities.

2. BACKGROUND

Identifying suitable locations for onshore wind turbines requires the assessment of a range of largely geospatial parameters. As a result, there has been extensive use of Geographic Information Systems (GIS) which are designed to capture, store, manipulate, analyse, manage, and present spatial or geographic data (Malczewski, 2004). Such GIS approaches often paired with Multi-Criteria Decision Analysis (MCDA) to provide a method to interpret the geospatial data and rank potential options from the model data.

Early developments in onshore wind GIS-MCDA modelling started in the late 1990s (Voivontas *et al.*, 1998; Baban and Parry, 2001). In recent years, there has been significant international interest to model wind turbine site suitability, and a large number of methods have been developed (Janke, 2010; SQW Energy, 2010; Sliz-Szkliniarz and Vogt, 2011; Van Haaren and Fthenakis, 2011; Gass *et al.*, 2013; Neufville, 2013; Wang *et al.*, 2014; Miller and Li, 2014; Atici *et al.*, 2015; Watson and Hudson, 2015; Noorollahi *et al.*, 2015; Gove *et al.*, 2016). These models typically are formed of the stages as shown in Figure 1. Firstly, input parameters are selected covering environmental, technical and social (Gigović *et al.*, 2017). For example, ideal sites are typically identified as having high average wind speeds; not being close to urban areas; not in protected landscapes (e.g. National Parks); not close to airports (to minimise radar interference); close to roads for access and finally close to power lines for grid connection. Each location is then scored against these input parameters, and incompatible areas are excluded from further analysis, such as areas which have already been developed (roads and buildings).

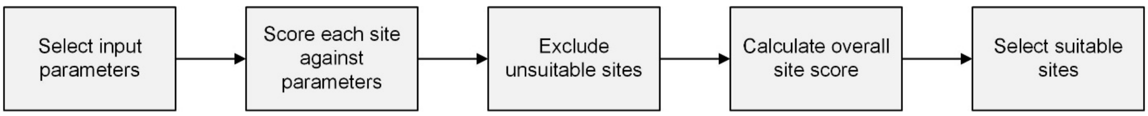

Figure 1 An overview of the typical structure of GIS-MCDA methodologies

For remaining sites which could be developed, a score is calculated to assess the overall suitability of the site. While several techniques are used, the Weighted Sum Method (WSM) is most typically used as a method to combine the different layers into a single score as follows:

$$Site\ Score = \sum w_i a_i \ \ for\ i = 1, 2, 3 \ldots\ N \qquad (1)$$

where w is the parameter weighting, a is the parameter value and i is the attribute layer in the model. This rating can then be used to determine the most suitable sites for development.

A concern surrounding the WSM is that the method is often applied without any insight into the meanings of two critical elements: the weights assigned to attribute layers and the procedures for combining the layers (Malczewski, 2004). While methods such as the Analytic Hierarchy Procedure (AHP) are used to mitigate this (Watson and Hudson, 2015), models remain highly sensitive to the weightings used, and there are concerns that models result provide the sub-optimal location of wind turbine locations, as demonstrated by the high level of projects being refused planning permission within the UK.

To address concerns of parameter weighting, there has been increased interest in quantitatively assessing which parameters influence the likelihood of wind turbines receiving planning permission (van Rensburg *et al.*, 2015). This approach has recently been integrated within GIS modelling to assess the influence of geospatial parameters in the UK (Harper *et al.*, 2017). This can be considered as a form of retrospective GIS analysis, where the existing spatial distribution of sites is assessed to enable prediction of where future turbines may be acceptable. Harper et al's results suggest that the 1) the number of wind turbines; 2) percentage of the local population with high levels of qualifications; 3) the average age and 4) local political composition emerge as key influences affecting planning approval, while other typically used parameters such as proximity to urban areas appear less influential. However, these finding have yet to be integrated into a GIS-MCDA.

Finally, the issue of the standardisation of non-commensurate criteria within the WSM and GIS-MCDA has yet to be satisfactorily addressed. To create a single site suitability score requires the combination of a range of economic, environmental and social parameters which cannot directly be summed together into a single scale. Methods such as the linear transformation method are often used to standardise each variable, but there is limited empirical justification for such approaches (Jiang and Eastman, 2000).

This paper addresses these concerns and presents the results of a GIS-MCDA model that integrates planning acceptance rates into modelling. This approach builds upon our previous work and demonstrates an alternative layered approach combining non-commensurate parameters, in particular avoiding the use of linear transformations within the MCDA.

3. METHODOLOGY

The overall structure of the GIS model is shown in Figure 2, and the stages are described in the following subsections.

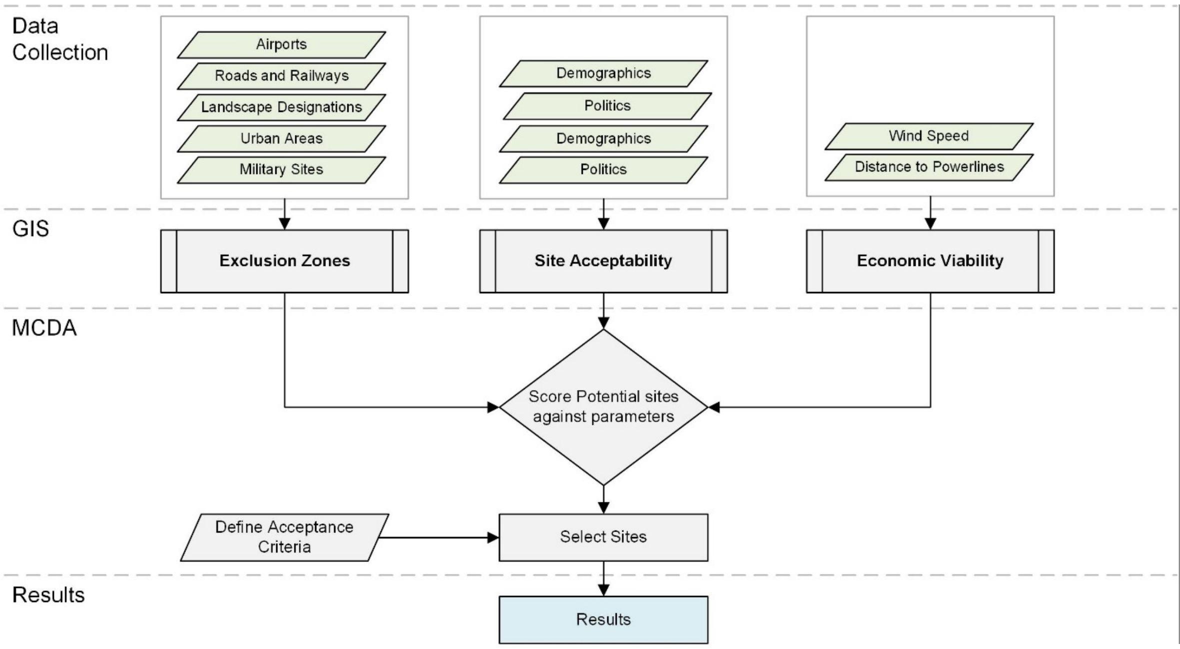

Figure 2 Overview of the onshore wind GIS-MCDA Structure

3.1. Model formation

A preliminary scoping study was conducted to formulate the model and identify parameters which influence wind turbine developments. The identification of criteria involves a systematic analysis of factors that may impact installation of the wind farms. This considered a range of academic work as listed in Section 2, consultancy reports (Land Use Consultants, 2010; SQW Energy, 2010) and wind turbine planning guidance (Smith, 2016).

The study was conducted across Great Britain (England, Scotland & Wales). This was chosen because of the broadly similar categorisation of land types, nature designation, data availability and legislation across these regions. To allow for a more detailed understanding of the local effects, this paper also highlights the results from two case study areas, Solent and the Midlands, as shown in Figure 3. These two areas were selected as there are large differences in the number of wind turbines deployed, with no wind turbines near Solent while 30 projects have been constructed within the Midlands region (DECC, 2016).

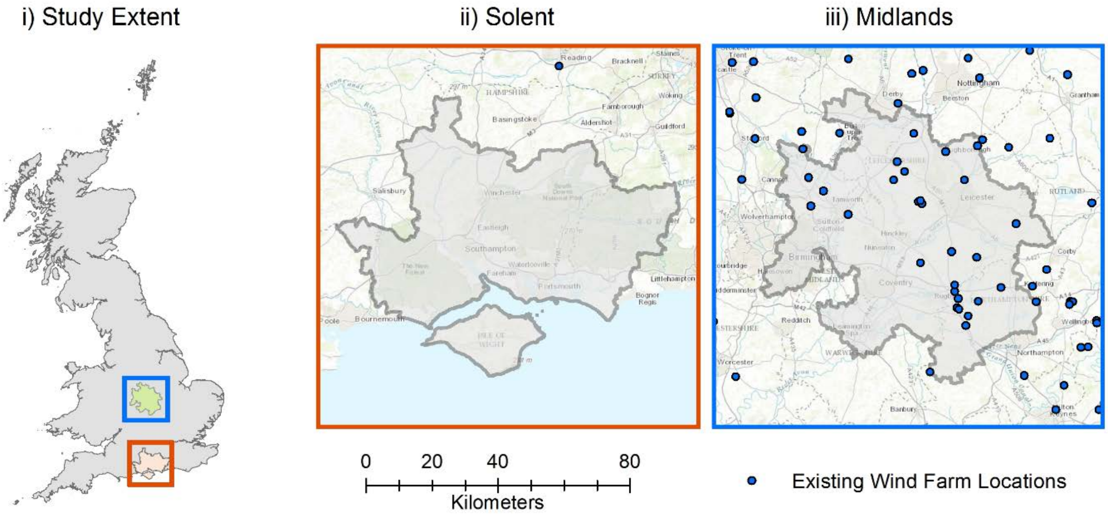

Figure 3 Analysis Extent and regions selected for case studies, highlighting the locations of existing wind turbine projects.

Once key parameters were identified, relevant data was collected from a range of sources for geospatial (Ordnance Survey, 2016; OSM, 2016), environmental (SNH, 2015) and demographic variables (Office for National Statistics, 2016). A full explanation of the datasets is available within the previous work (Harper *et al.*, 2017).

3.2. GIS Model

As highlighted within the background literature, there are challenges in combining non-commensurate data within MCDA. Instead of combining variables into a single score, an approach was developed to group input variables into layers based on their type of influence on a site suitability, with three layer GIS layers being formed; 1) *Site acceptability*; 2) *Exclusion zones* and 3) *Economic viability*. These are explained in more detail as follows.

Site acceptability assess whether the chance of the location receiving planning permission. This layer is based on previous analysis which used logistic regression methods to identify the key influential parameters that determine whether a wind turbine successfully obtained planning consent (Harper *et al.*, 2017). An overall predictive accuracy of 63% was achieved with the model, with the most influential parameters shown in Table 1. The Odds Ratio shown indicates how much the predicted planning acceptance rate changes for each unit of the parameter. For example, for each km a site is further away from an urban region, its likelihood of receiving planning approval increases by 0.176%.

Table 1 Parameters determined to influence the planning acceptance of wind turbines

Parameter	Unit	Odds Ratio	Note
Turbine Capacity	MW	0.311	Set as 2MW (a single turbine)
Urban Regions	km	0.176	Expressed as kilometre to each feature
AONB	km	0.009	
National Parks	km	0.007	
RAMSAR	km	-0.008	
SPA	km	-0.012	
Qualification Perfect Level 4	% of Population	-0.031	
Mean Age	years	-0.052	
Time of Construction	years	-0.110	Assumed to be 2017 within the model

Exclusion Zones considers whether the site can be used for development. Existing legislation and ecological guidance was reviewed, and the geospatial development patterns of existing wind farms were assessed to identify whether specific regions were avoided by developers. These criteria were split into the following taxonomy:

- **Hard Planning Criteria**: these are legislative restrictions that prevent the development in specific areas. For example, wind turbines must not be built within a toppling distance of main roads.

- **Soft Planning Criteria**: these are derived from statistical analysis of existing wind turbine planning applications to understand regions where turbines were generally not proposed but not legislatively restricted. For example, while it is technically possible to build in National Parks, only two projects have been built within them and therefore these regions can be considered as non-developable areas. This also excludes sites of ecological protection.
- **Buffer Criteria**: explores whether there is any geospatial trend for sites to be located away from certain features. For example, wind turbines sites are not banned near airports, but sites are skewed away from these sites suggesting planners aim to keep distance between the sites.

The values used within each of the exclusion layers are shown Table 2. Based on these three categories, three scenarios were formed to assess the impact of planning restrictions on the development potential: 1) *Low Restriction* (Hard Planning Criteria only) 2) *Medium Restriction* (Hard & Soft Planning Criteria) and 3) *High Restriction* (Hard, Soft and Buffer).

Table 2 Parameters and exclusion distances used within the model

Parameter	Exclusion Distance (km)		
	Hard Planning Criteria	Soft Planning Criteria	Buffer Criteria
Airports	0	2	10
Roads	0.15	0.15	0.15
Railways	0.15	0.15	0.15
Military Sites	-	0	10
Urban Areas	-	0	2
Powerlines	0.15	0.15	0.15
Landscape Designations[1]	-	0	2
Nature Designations[2]	-	0	2

Notes:
1: National Parks, Areas of Outstanding Natural Beauty, Heritage Coast
2: (National Nature Reserves (NNR), Natura 2000, Special Protection Areas (SPA), Sites of Special Scientific Interest (SSSI))

Finally, *economic suitability* of the potential financial return of the site. This layer was determined based on the wind speed and proximity of the site to the distribution network. Potential wind power output was calculated using the Weibull probability distribution combined with logarithmic hub height correction.

Each of the layers were calculated as a raster layer, with a spatial resolution of 250 metres, and were analysed and integrated using R and supporting geospatial packages *raster* (Hijmans, 2016) and *sp* (Roger S. Bivand, Edzer Pebesma, 2013).

3.3. Multi-Criteria Decision Analysis

The model considered the suitability of a site for the installation of single wind turbines, and was based on a 2MW wind turbine which represents the average size of onshore turbines constructed in 2016 (Vestas, 2017). Based on planning guidance, a spacing between turbines of 500m was used (Smith, 2016), resulting in a development density of 8MW/km^2.

As shown in Figure 4, each site is categorised based on its Economic viability (X-axis) and Site Suitability (Y-axis), with four types of suitability defined (Low/Potential/Good/Excellent). More flexibility is given to the site suitability parameter to reflect that there is less certainty to this value. The analysis selected sites based on their suitability rating. To estimate the potential capacity of sites that could be developed, all sites that score "Excellent" or "Good" were selected as suitable for development.

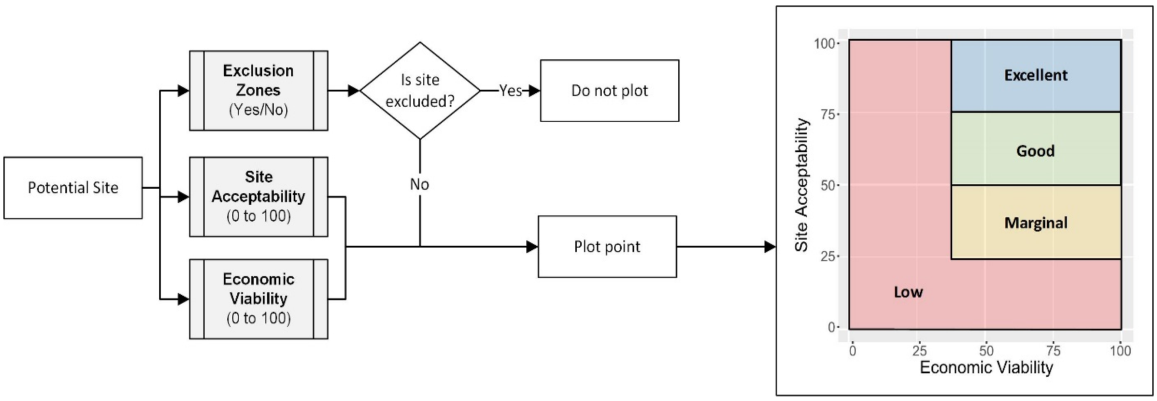

Figure 4 Classification of potential sites based on the GIS layer results

4. RESULTS

The results from the geospatial model layers are presented in Figure 5, which shows the three separate layers of the analysis. These layers are combined to determine the site suitability score displayed under the medium development restriction scenario, as shown Figure 6. Nationally, it can be seen from the results that sites appear to be more suitable within Scotland, the South East of England, and patches of West England. For the Solent region, 77% of the land was excluded with no sites being deemed "Good" or "Excellent" for wind development. In comparison, 45% of the Midlands region was excluded for development with 1.2GW of potential site capacity identified from suitable sites.

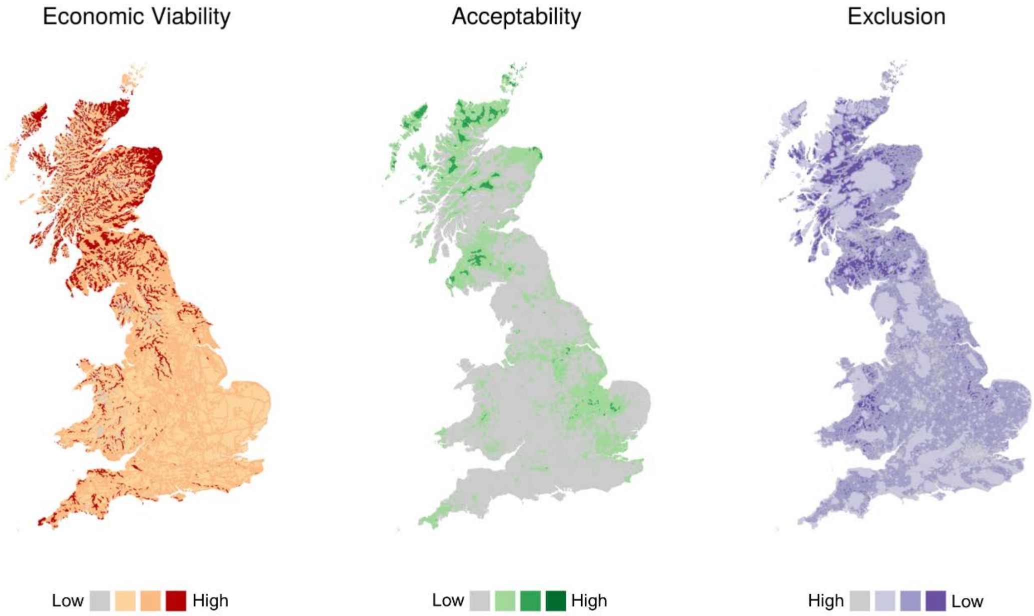

Figure 5 Results for the three onshore wind GIS layers within the model. Darker colours indicate desirable characteristics for wind turbine sites.

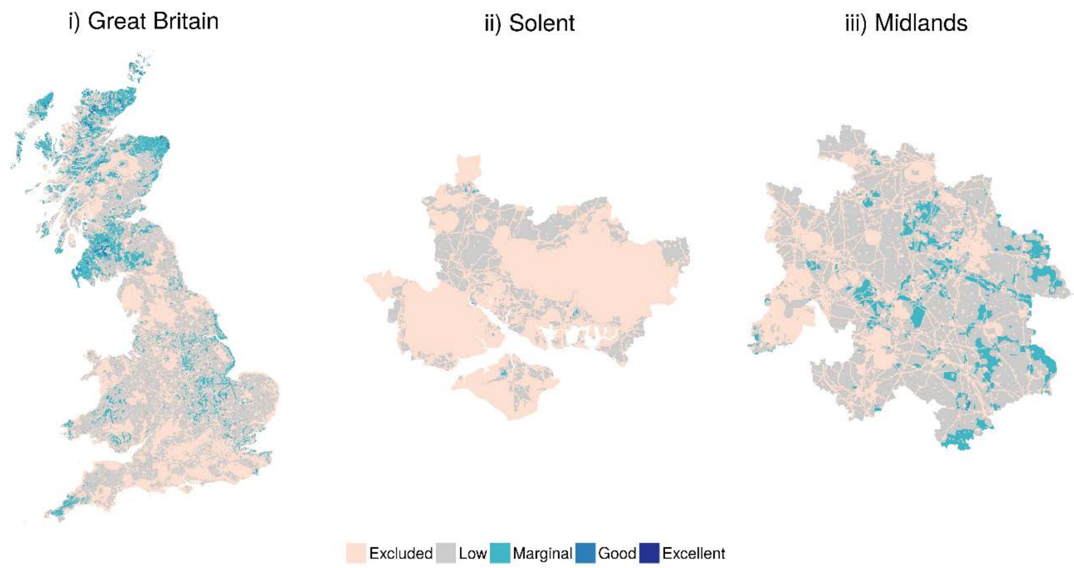

Figure 6 Comparison of Wind Turbine Potential under the medium development scenario

Table 3 provides a detailed breakdown of the land suitability under of the each of the three exclusion regions for the national model. Cells highlighted in grey indicate those which are the most suitable for development potential, being outside crucial exclusion zones and having a high site suitability score. Such sites cover 0.74% of the country, and represents 13GW of potential capacity if fully utilised.

Suitability Score	Hard Criteria	Soft Criteria	Buffer Criteria	No Exclusion	Total
Low	11.43	25.58	37.70	2.82	77.5
Marginal	2.78	5.90	8.98	3.07	20.72
Good	0.07	0.93	0.51	0.23	1.74
Excellent	0	0.005	0.003	0	0.008
Total	14.275	32.418	47.186	6.12	100

Table 3 Site score suitability matrix comparing exclusion criteria against site suitability, coverage of land covered by each classification. Cells highlighted in grey indicate the most suitable for development.

The comparative suitability of the regions can also be explored through density plots as shown in Figure 7. Each non-excluded site is represented as a point, and the regional variation in acceptability and economic viability can be viewed on separate scales. The site acceptability within the Solent region is generally less than the national average and Birmingham, although the economic viability is generally similar.

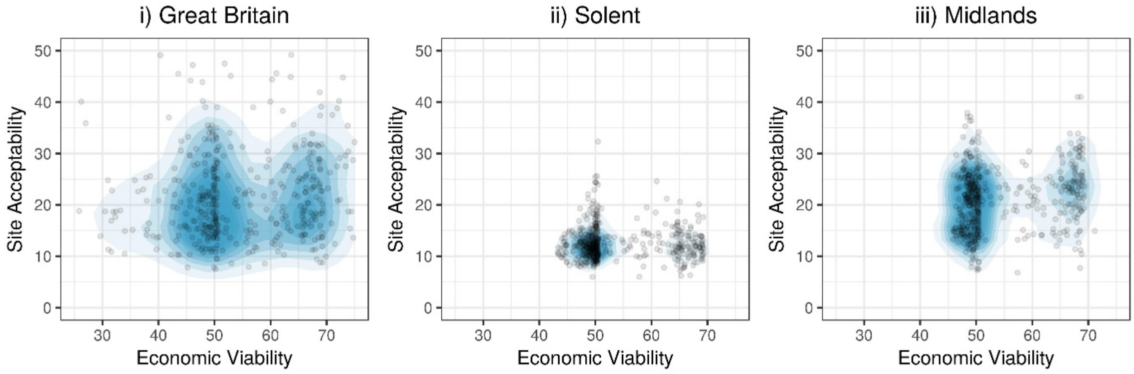

Figure 7 Two-dimensional Density Plots for wind turbine sites within the Birmingham and Hampshire/Solent regions. Note that the axes have been truncated at a score of 50.

5. DISCUSSION

The analysis suggests that 13GW of onshore wind would be highly suitable within a medium development restriction scenario, which considered the “hard” and “soft” planning criteria. If the stricter “buffer” criteria are met, the estimated capacity is reduced to 4 GW. Both these estimates are significantly lower than previous studies which have suggested total capacity could exceed 200 GW (Stoddart and Turley, 2012; Gove *et al.*, 2016). This highlights the impact of considering likelihood of planning acceptance within the GIS-MCDA and the constraint this places on development.

The case studies of Solent and Midlands highlight the regional variations in onshore wind potential resource as shown in Figures 6 and 7. From a resource perspective, the Solent area is highly suitable with many hilly regions and its coastal location resulting in high wind speeds. However, the opportunity for development is limited by National Parks and Areas of Outstanding Natural Beauty (AONB), and the sites that are located outside of these regions are largely unsuitable for development due to the demographic composition. In comparison, the Birmingham region faces much less restriction in where developments could be made and presents much greater opportunity for future development.

The results further highlight that cost is not the dominant issue in determining the suitability of a wind turbine site, as wind speeds are largely satisfactory and in UK most sites are an acceptance distance to powerlines for a wind turbine to be economic. A number of previous studies have placed a high weighting on wind resource (Shirgholami *et al.*, 2016), reflecting the interest of the developer to maximise returns. In reality, it may be in their interest to select a less windy site that is more likely to receive planning permission.

On a national level, it is important to consider the distribution of potential sites and the consequent impact this may have on the electricity transmission network. The results indicate that regions in Scotland and the South West are most suitable for further development; however, such areas are distant to large load centres such as cities, requiring transmission networks or energy storage to be upgraded.

A benefit of building the model into several intermediate layers, such as used in this model, is that it allows the results to be more easily interpreted and minimise the concerns surrounding standardisation of parameters. When combining the variables into a single suitability score, it can easily hide or distort what is influencing the site score, and make it difficult to understand why some sites are more suitable than others are.

5.1. Limitations & Future Work

Such models are highly influenced by the availability and quality of the data for the analysis. Wind speed is only available at 1km resolution and does not account for roughness of surface caused by urban developments of varying land cover such as forests (DTI, 2001). The errors from any dataset will have propagated through the analysis and, combined with errors from other layers, may cause inaccuracies in the output map. Future work will therefore investigate the sensitivity of results.

Whilst the analysis has tried to understand the chance of a project being accepted, it has only considered geospatial parameters. As previous studies have highlighted, such parameters in themselves only provide part of the explanation as to why wind farms are accepted (Toke, 2005; Langer *et al.*, 2016). Greater emphasis must also be placed on the planning process and local engagement of a wind project if it is to be successful at planning.

The analysis has also not considered the impact of electricity transmission networks, and the potential requirement of grid reinforcements. It is already being seen in the UK that grid reinforcements are being made to transfer electricity and this is becoming a limiting factor in the development of renewable energy projects (National Grid, 2015). The majority of sites identified as suitable for development are distant from large load centres, and therefore would place additional strain on the transmission network to transfer this electricity across the country. It is therefore important that this issue is explored further in future analysis.

The model only considers the suitability of individual wind turbines, and does not assess whether an area is suitable for development of a larger wind farm. There would be economies of scale in proposing a single larger development, and as such, these locations would be preferential to developers.

The analysis did not consider the influence of the cumulative number of wind turbines within a certain area. It is not fully understood within literature whether there is a limit to the development potential of wind turbines, although some evidence suggests that regions can reach a saturation level (Toke *et al.*, 2008).

6. CONCLUSION

The authors' have presented a GIS-MCDA which can be used to assist in location onshore wind turbines. By integrating planning acceptance rates into the decision-making process, the results of this model have highlighted that the potential resource is significantly lower than previous estimates. However, there remains an opportunity for further development of onshore wind turbines to help meet renewable electricity generation targets.

The GIS-MCDA presented an alternative method of combining non-commensurate data into the decision-making process. By avoiding the use of standardisation, there is less distortion to the input data and this reduces potential errors within the model results. This also provides greater insight into the model results as it is easier to understand the factors influencing site suitability.

Using two case studies, the results have shown how the onshore wind capacity can vary significantly for similar types of regions within the same country. This can be influenced by physical restrictions such as landscape and nature designations, or "hidden" factors such as local demographics and political composition. It is therefore important that these factors are understood when wind turbines are being considered within a region.

The findings of this study can be used by a range of stakeholder to improve the planning and development of wind turbines. As examples, regional planners could more accurately estimate the potential capacity within their region, and project developers could gain a greater understanding of where sites should be proposed to increase the likelihood of receiving planning permission. The results should support, not replace, local level planning.

Whilst the analysis was completed within Great Britain, the concepts developed can be applied internationally. However, the specific planning acceptability data will have to be the region as outlined in previous analysis (Harper *et al.*, 2017).

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8. SUPPORTING DOCUMENTS

The analysis was completed using R and the full analysis is provided here: https://github.com/mikey-harper/SET2017Paper.

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Glossary

Energy Neutrality "the extent to which a district can supply itself with sustainable energy generated within the boundaries of that district.

Energy Autarky an energy system which operates entirely isolated, without external assistance or interconnection.

Urban Hinterland the rural area surrounding cities, and the transition zone where urban and rural uses mix and often clash..

NIMBY a person who objects to the siting of something perceived as unpleasant or hazardous in their own neighbourhood, especially while raising no such objections to similar developments elsewhere.

Spatial Scale The geographic coverage at which spatial measurement measurement is conducted or planned.

Spatial Nonstationarity is a condition in which a simple global model cannot explain the relationships between some sets of variables.

Territoriality the attempt by an individual or group to affect, influence, or control people, phenomena, and relationships, by delimiting and asserting control over a geographic area..

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