The impact of climate change on the levelised cost of wind energy

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**Abstract**

Society’s dependence on weather systems has broadened to include electricity generation from wind turbines. Climate change is altering energy flows in the atmosphere, which will affect the economic potential of wind power. Changes to wind resources and their upstream impacts on the energy industry have received limited academic attention, despite their risks earning interest from investors.

We propose a framework for assessing the impact of climate change on the cost of wind energy, going from the change in hourly wind speed distributions from radiative forcing through to energy output and levelised cost of electricity (LCOE) from wind farms. The paper outlines the proof of concept for this framework, exploring the limitations of global climate models for assessing wind resources, and a novel Weibull transfer function to characterise the climate signal.

The framework is demonstrated by considering the UK's wind resources to 2100. Results are mixed: capacity factors increase in some regions and decrease in others, while the year-to-year variation generally increases. This highlights important financial and risk impacts which can be adopted into policy to enhance energy system resilience to the impacts of climate change. We call for greater emphasis to be placed on modelling wind resources in climate science.

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1. Introduction

Energy policy has always been impacted by uncertainty in future resource availability and cost; the volatility of gas prices (early 2000s) and oil prices (mid-2010s) only reinforce this critical link. Understanding how the cost of energy infrastructure as a whole may change over time can allow policy to be directed to redress pervasive aspects of the market. Issues pertaining to renewable energy infrastructure should not be immune from this critique, including stranded assets [1].

Of the many effects that climate change will have on Earth's weather systems, its impacts on wind resources and the wind energy industry have received limited attention. Traditionally the primary focus of climate models has been temperature and precipitation; however our dependence on the weather for energy supply is strengthening in the wake of COP21 as the international community redoubles its efforts in mitigating climate change. Some 3% of global electricity and 7% in Europe is harvested from atmospheric motion [2], so the need to assess this resource in this nuanced context is gaining traction.

Climate change is expected to modify the spatial and temporal characteristic of current wind speeds: turbulence (changeability), direction (prevalence), extreme events, frequency, density and temperature [3,4]. Climate model projections show wind speeds changing heterogeneously [5,6] with wind resource potentials increasing in some areas whilst reducing in others [7]. As wind energy scales with the cube of its speed, slight changes in these characteristics are magnified in the extractable energy output [8].

Wind energy economics are characterised by relatively high capital expenditure (capex) and low operational expenditure (opex). The average cost of energy from wind, known as the levelised cost of electricity (LCOE), scales with a 1:1 inverse relationship to the amount of wind available when all other variables remain constant. Changes in the wind's availability will therefore have a significant impact on the cost of electricity from wind power.

Investment in wind power is mired with uncertainty, from energy policy and financial subsidies to forecasting its variability. Measures that can reduce associated risks and their costs will therefore improve the deployment of this climate change mitigation measure. Wind farms must compete with conventional fossil fuels on the electricity market [9]. A framework is proposed in this paper to assist in the future-proofing of wind farm portfolios and lay the foundations for a tool to provide a due diligence mechanism to statistically represent investment risk when siting assets. Such a
tool could ultimately influence the cost of capital and enhance sustainable investments [10,11].

Academics are increasingly using interdisciplinary approaches towards these issues around wind energy, scoping more stakeholders in their studies [12]. Very few have considered the entire research-chain that is required to assess the impact of climate change on the cost of wind energy; which encompasses climate science, engineering, energy economics and policy disciplines [13].

Increased wind energy potentials may not directly lead to greater energy revenues or a stronger impetus to invest [14]. This non-linear response is due to the complex nature of electricity markets [15]. Incorporating this into the evaluation of how wind resources may vary under different climate scenarios enables better scope of what interdisciplinary boundaries exist between different stakeholders and experts, primarily between power engineers and climate scientists.

There are two aims of this paper. Firstly to identify and highlight knowledge gaps that exist across the interdisciplinary spectrum of climate science and energy systems research. To this end, Section 2 reviews the current state of knowledge across these disciplines, and Section 3 presents a framework to resolve the information gaps via coupling climate model outputs with a techno economic model. The second aim is to investigate whether climate change will alter the UK’s wind resource and the economic implications this may have for wind power in the future. This paper goes on to demonstrate this framework using publicly available data from a single run of a climate model. Sections 4 and 5 determine whether there is a difference between observed and projected probability distributions of wind profiles at specific sites within the research area under different scenarios; and evaluate the economic feasibility of using the wind resource under different scenario conditions.

2. Background

2.1. Wind resources

2.1.1. The UK’s wind resource

The UK has substantial wind resources compared to other European nations [16], which it intends to increasingly utilise for low carbon electricity [17]. The UK’s location at the crossroads for many mid-latitude air currents provides a variety of non-extreme weather phenomena [18]. It is buffeted by the thermally moderating nature of the Atlantic Ocean and its Gulf Stream (west), the European continental landmass (east) and Arctic air masses (north) [19].

Within the UK and its exclusive economic zone (EEZ), the northern regions (Scottish Islands and North Atlantic) are significantly windier than the south. Coastal and offshore areas also experience higher mean wind speeds than inland, primarily due to impact of topography and its thermal properties causing pressure heterogeneities which induce winds [18]. This is reflected in the distribution of wind farms across the UK (Fig. 1), which are predominantly in the central belt of Scotland and off the east coast of England.

Due to the UK’s mid-latitude position, the seasons impact on wind resources by changing how energy is delivered and redistributed. A primary mechanism is extratropical cyclone formation, where low pressure storm systems form in the mid-Atlantic and travel towards the UK along a storm track [20]. As this mechanism is enhanced due to the increased temperature gradient in winter, average wind speeds are 50% higher in winter than summer, at 9.2 cf. 6.2 m/s [21,22]. Speeds are higher during the day than at night, which is exacerbated in summer due to fewer low pressure systems and a greater difference between day and night temperature gradients [18].

Due to both external climate forcing and internal chaotic atmospheric phenomena there has been natural variation in the UK’s wind resource over past centuries [16]. The North Atlantic Oscillation (NAO), Arctic Oscillation (AO) and long-term persistence (LTP) can skew wind speeds within their natural variable range due

<table>
<thead>
<tr>
<th>List of abbreviations</th>
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<tbody>
<tr>
<td>AEP annual energy production</td>
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<tr>
<td>BADC British Atmospheric Data Centre</td>
</tr>
<tr>
<td>CMIP5 Coupled Model Inter-comparison Project 5</td>
</tr>
<tr>
<td>Capex capital expenditure</td>
</tr>
<tr>
<td>CF capacity factor</td>
</tr>
<tr>
<td>IPCC Intergovernmental Panel on Climate Change</td>
</tr>
<tr>
<td>LCOE levelised cost of electricity</td>
</tr>
<tr>
<td>MERRA modern era retrospective-analysis for research and applications</td>
</tr>
<tr>
<td>ESM2G (NOAA GFDL) National Oceanic and Atmospheric Association: Geophysical Fluids Dynamics Laboratory — Earth System Model 2</td>
</tr>
<tr>
<td>Opex operational expenditure</td>
</tr>
<tr>
<td>RCP representative concentration pathways</td>
</tr>
<tr>
<td>RMS root mean square</td>
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</table>
to the impact these atmospheric phases have on the intensity and direction of the extratropical cyclone storm track. This is evident in 2010 when the UK experienced its lowest wind year for decades due to the NAO’s impact on shifting storm systems away from the UK [19,23].

2.1.2. Research on climate change and wind

Climate models are a critical tool for understanding wind resources, vital to the longevity of the industry and climate targets [24,25]. Numerous locales have been assessed when analysing the impact of climate change on wind resources: the US [26]; South Korea [27]; Brazil [28]; and Northern Europe [6] have seen large interest, unsurprisingly due to the economic potential of the resource that exists. These studies primarily focus on changing wind speeds, and reach high level regional considerations of the climate change impact on energy potentials. Wind resources may have their beginnings in global circulation but are primarily shaped by their site [8].

The UK’s wind speeds are particularly difficult to project, as they depend on simulating competing atmospheric phenomena that are not fundamentally understood [25]. Extrapolating this to the future increases this difficulty [23,29,30]. Nonetheless, research is pushing these boundaries to understand the resource and its dynamism [5]. UK wind resources are expected to change seasonally, increasing in winter and decreasing in the summer [4,31], possibly due to winter cyclonic activity increasing the associated mean storm winds [32–34]. Others also attribute resource change to modifications of the NAO [19]; LTP [23]; mean sea level pressure gradients [7]; and also effects of alterations to the Atlantic meridional overturning circulation [35,36]. Causation cannot be exclusively attributed to any of these theories until more is understood about the climate system [33].

Previous assessments of the UK’s wind regime has shown a change in the gradient from the north to the south; increasing mean wind speeds closer to the North Atlantic and decreasing in the south closer to Europe [24], exaggerating the current gradient in wind speeds [24]. Seasonal intensification is evident in varying scenarios, highlighting the need to better understand the implications of greater variability in wind resources on energy supply. Interannual variability of mean wind speeds is also projected to change, with a slightly higher increase in the southeast of England; again confounding the effect of seasonality [31].

Climate modelling and projecting specific variables into the future is fraught with uncertainties and sources of error [30]. The interactions between the atmosphere and hydrosphere coupled with both topography and a biotic component can prove difficult to simulate due to the complex nature of their interconnected relationships [37]. This is confounded by the various parameterisations of model features in use, as each research centre estimates values for modelling variables according to their conventions, resulting in a plethora of models, scenarios and runs [38]. Improvements in modelling should lead to improvements in wind resource comprehension [37].

2.2. Wind power

Similar to conventional power plant, wind turbines only generate electricity under a satisfied set of criteria; notably, winds need to be within the cut-in and cut-out speeds [8]. There is no simple linear response between mean annual wind speed and power output, so this must be modelled from first principles.

2.2.1. Historic wind resources — reanalysis data

Traditionally, wind resource assessments were conducted using empirical data collected from met masts at high temporal resolution, bespoke to the site and purpose of investigation [39]. Many studies have used hourly wind speed data recorded by met masts at varying heights from the ground [22,40–42]. Hourly met mast speeds have been directly compared to metered wind farm load factors in Northern Spain and Scotland, showing that accurate estimates can be made for monthly energy generation, but not for hourly power outputs [43,44]. These datasets, although detailed, have limited applications to other sites due to their limited spatial and temporal scale.

One means of addressing this challenge is using reanalyses as a source of wind speed data: atmospheric boundary layer models which process physical observations from met masts and other sources into a coherent and spatially complete dataset, often global in extent and spanning several decades. The first uses of reanalyses for wind power appeared in 2009 [45,46], and the technique is rapidly gaining popularity for simulating wind output across Europe [47,48], the US [49] and globally [50]. Numerous studies have confirmed reanalysis to be more accurate than met masts for modelling national aggregate wind power output in the UK [21,51–55], Denmark [56] and Sweden [57], and in work currently under submission, across the whole of Europe [58].

Sharp collates the results of 16 studies using reanalysis, finding that the correlation between measured and simulated wind speed average Pr = 0.81 ± 0.06 for onshore and 0.88 ± 0.05 for offshore sites [53]. Staffell and Green showed that monthly output from Britain’s aggregate wind fleet can be simulated to an accuracy of ±0.8%, and half-hourly output to within ±4.5% [54,55]. The national fleets in other countries can be simulated with root mean square errors (RMSE) of between 3.1% and 7.4% on hourly output [58]. At present, no reanalyses produce data with a higher resolution than hourly, so statistical techniques are required to synthesise higher-resolution data such as 10 min, which may impact on the frequency distribution of modelled speeds [59]. Similarly, while global reanalyses can be adequate for simulating wind output over large spatial scales (e.g. at national level), they are incapable of more detailed wind resource characterisation due to topography or turbulence in winds; and must be complemented by more detailed meso-scale and micro-scale modelling [58].

The global atmospheric circulation models that underpin reanalyses are fundamentally similar to climate change models, being calibrated to historic observations of the weather system in an attempt to better simulate and understand complex meteorological interactions. Reanalyses produce data that is comparable to global climate models, typically giving the northerly and easterly component of wind speeds at 10 m above ground in a format such as NetCDF or GRIB. This makes it more convenient to process climate model data with tools such as the Virtual Wind Farm model to study energy system impacts, which has to the best of our knowledge not been performed to date.

Several reanalysis products are available, as listed in Table 1. Wind speeds are most commonly available at a fixed height of 10 m above ground, only MERRA and ERA-20C provide other heights closer to those used by wind turbines. Wind speed variables are also available at other model heights, usually based on fixed pressure or isothermal levels. The height of these levels above ground is not constant, and often well outside the region of interest, above 250 m or below 0 m (the latter is purely hypothetical, e.g. the height at which air pressure would equal a set value).

2.2.2. Projected wind resources — climate model outputs

Climate modelling capabilities and understanding has developed significantly over recent years with larger and faster computers enabling more complex calculations to be undertaken. One of the most recent examples of climate modelling exercises centre around the fifth Coupled Model Inter-comparison Project (CMIP5)
century temperature rises of 1.0, 1.8, 2.2 and 3.7 °C. These numbers represent the extent of Europe.

For context, the average UK wind farm has a capacity factor of 29.0% or 2540 full load hours per year [58], which translates to around 100 GWh per year of electricity produced from a 40 MW wind farm. The UK’s onshore farms average 26%, and offshore farms average 36%.

Time series of wind speeds are available at hourly resolution spanning several decades, giving a comprehensive but unmanageable quantity of data. It is common practice to simplify the underlying distribution of these speeds as a Weibull distribution [43,63]. This introduces some error in the resulting estimations of annual energy yield, as the Weibull approximation will differ from the true distribution.

Table 1
Overview of publicly available reanalysis datasets and the parameters most relevant to wind power synthesis.

<table>
<thead>
<tr>
<th>Institution/Model</th>
<th>Released</th>
<th>Coverage</th>
<th>Spatial resolution (lat × lon, degrees)</th>
<th>Time resolution (hours)</th>
<th>Wind speed heights</th>
<th>Other model heights</th>
</tr>
</thead>
<tbody>
<tr>
<td>ECMWF/ERA-40</td>
<td>2004</td>
<td>1957–2002</td>
<td>1.125 × 1.125</td>
<td>6</td>
<td>10 m</td>
<td>60</td>
</tr>
<tr>
<td>ECMWF/ERA-Interim</td>
<td>2006</td>
<td>1979–present</td>
<td>0.75 × 0.75</td>
<td>6</td>
<td>10 m</td>
<td>60</td>
</tr>
<tr>
<td>ECMWF/ERA-20C</td>
<td>2012</td>
<td>1900–2010</td>
<td>1.125 × 1.25–2.5</td>
<td>3</td>
<td>10, 100 m</td>
<td>91</td>
</tr>
<tr>
<td>JMA/JRA-25</td>
<td>2004</td>
<td>1979–2004</td>
<td>1.125 × 1.125</td>
<td>6</td>
<td>10 m</td>
<td>40</td>
</tr>
<tr>
<td>JMA/JRA-55</td>
<td>2013</td>
<td>1958–present</td>
<td>0.5625 × 0.5625</td>
<td>6</td>
<td>10 m</td>
<td>60</td>
</tr>
<tr>
<td>NASA/MERRA</td>
<td>2009</td>
<td>1979–present</td>
<td>0.5 × 0.667</td>
<td>1</td>
<td>2, 10, 50 m</td>
<td>72</td>
</tr>
<tr>
<td>NASA/MERRA v2</td>
<td>2015</td>
<td>1980–present</td>
<td>0.5 × 0.625</td>
<td>1</td>
<td>2, 10, 50 m</td>
<td>72</td>
</tr>
<tr>
<td>NCEP/R2</td>
<td>2001</td>
<td>1979–2012</td>
<td>2.5 × 2.5</td>
<td>6</td>
<td>10 m</td>
<td>28</td>
</tr>
<tr>
<td>NCEP/CSR</td>
<td>2009</td>
<td>1979–2010</td>
<td>0.5 × 0.5</td>
<td>6</td>
<td>10 m</td>
<td>6</td>
</tr>
<tr>
<td>NCEP/CSRv2</td>
<td>2011</td>
<td>2011–present</td>
<td>0.5 × 0.5</td>
<td>6</td>
<td>10 m</td>
<td>6</td>
</tr>
<tr>
<td>NOAA/20CRv2</td>
<td>2010</td>
<td>1871–2011</td>
<td>2 × 2</td>
<td>6</td>
<td>10 m</td>
<td>28</td>
</tr>
</tbody>
</table>

Table 2
Overview of global climate model data sets.

<table>
<thead>
<tr>
<th>Model</th>
<th>Modelling centre</th>
<th>Spatial resolution (lat × lon, deg)</th>
<th>Temporal resolution</th>
<th>Available RCPs</th>
</tr>
</thead>
<tbody>
<tr>
<td>BCC-CSM1.1 (m)</td>
<td>BCC, China</td>
<td>1.1 × 1.1</td>
<td>x x x x x x</td>
<td>2.6 4.5 6.0 8.5</td>
</tr>
<tr>
<td>CanESM2</td>
<td>CCCma, Canada</td>
<td>2.8 × 2.8</td>
<td>x x x x x x</td>
<td>2.6 4.5 6.0 8.5</td>
</tr>
<tr>
<td>CMCC-CM</td>
<td>CMCC, Italy</td>
<td>0.7 × 0.7</td>
<td>x x x x x</td>
<td>2.6 4.5 6.0 8.5</td>
</tr>
<tr>
<td>CNRM-CM5</td>
<td>CNRM-CERFACS, France</td>
<td>1.4 × 1.4</td>
<td>x x x x x</td>
<td>2.6 4.5 6.0 8.5</td>
</tr>
<tr>
<td>FIO-ESM</td>
<td>FIO, China</td>
<td>2.8 × 2.8</td>
<td>x x x x x</td>
<td>2.6 4.5 6.0 8.5</td>
</tr>
<tr>
<td>GFDL-CM3</td>
<td>NOAA/GFDL, USA</td>
<td>2.5 × 2.0</td>
<td>x x x x</td>
<td>2.6 4.5 6.0 8.5</td>
</tr>
<tr>
<td>GFDL-ESM2G</td>
<td>NOAA/GFDL, USA</td>
<td>2.5 × 2.0</td>
<td>x x x x x</td>
<td>2.6 4.5 6.0 8.5</td>
</tr>
<tr>
<td>GFDL-ESM2M</td>
<td>NOAA/GFDL, USA</td>
<td>2.5 × 2.0</td>
<td>x x x x x</td>
<td>2.6 4.5 6.0 8.5</td>
</tr>
<tr>
<td>GISS-E2-H</td>
<td>NASA/GISS, USA</td>
<td>2.5 × 2.0</td>
<td>x x x x x</td>
<td>2.6 4.5 6.0 8.5</td>
</tr>
<tr>
<td>HadGEM2-ES</td>
<td>MOHC, UK</td>
<td>1.9 × 1.2</td>
<td>x x x x x x</td>
<td>2.6 4.5 6.0 8.5</td>
</tr>
<tr>
<td>INM-CM4</td>
<td>INM, Russia</td>
<td>2.0 × 1.5</td>
<td>x x x x x x</td>
<td>2.6 4.5 6.0 8.5</td>
</tr>
<tr>
<td>IPSL-CM5A-LR</td>
<td>IPSL, France</td>
<td>3.7 × 1.9</td>
<td>x x x x</td>
<td>2.6 4.5 6.0 8.5</td>
</tr>
<tr>
<td>MIROC-ESM</td>
<td>MIROC, Japan</td>
<td>2.8 × 2.8</td>
<td>x x x x x</td>
<td>2.6 4.5 6.0 8.5</td>
</tr>
<tr>
<td>MPI-ESM-LR</td>
<td>MPI-M, Germany</td>
<td>1.9 × 1.9</td>
<td>~ x x x x x</td>
<td>2.6 4.5 6.0 8.5</td>
</tr>
<tr>
<td>MRI-CGCM3</td>
<td>MRI, Japan</td>
<td>1.1 × 1.1</td>
<td>~ x x x x x</td>
<td>2.6 4.5 6.0 8.5</td>
</tr>
</tbody>
</table>

c Acronyms: 3 hourly, 6 hourly, daily, monthly, yearly. x denotes full availability, ~ denotes availability for some RCPs.
d Source: http://browse.ceda.ac.uk/browse/badc/cmip5.
the actual probability distribution function of wind speeds, but this error is random and unbiased [64].

Another useful parameter that describes the wind resource is the interannual variability (\( IV_{\text{annual}} \)), which represents how strongly wind speeds vary from year to year [31]. The standard deviation in annual mean speeds (\( \bar{v} \)) of the time frame is divided by the mean over the whole period:

\[
IV = \frac{\sigma(\bar{v})}{\bar{v}} \tag{2}
\]

Analogous to this is the interseasonal variability (\( IV_{\text{seasonal}} \)). An increase in the IV also increases the variability in the energy output of wind, impacting the revenue streams of wind energy projects.

2.3. Wind economics

Time and experience has improved the robustness of investment sources for wind power [15]. Primitive models of investment have been succeeded by portfolio management and balance sheet financing. Factors impacting the construction costs include: turbine (ex-works), foundation, mechanical and electrical installation, grid connection (including internal and main cable), consultancy, environmental analysis and project design, land, financial costs and wider associated infrastructural requirements such as roads, etc. [12]. Operating costs are related to: insurance, maintenance, repair, spare parts and administration [15,62]. These costs vary depending on each project's specifications.

2.3.1. Levelised cost of electricity (LCOE)

The LCOE is a useful economic metric for comparing the cost of different generation types, measured in terms of cost per unit energy output (€/MWh). This provides a single measure which encompasses capital, fuel, carbon and other costs and factors in resource availability. This simplicity, not withstanding its flaws, makes LCOE a popular metric across disciplines and within policy circles [65]. LCOE can be calculated by dividing the annualised cost of generation by the AEP as seen in Equation (3) [62]. LCOE is inversely proportional to AEP; if wind resources increase whilst the total cost remains constant, then the cost per unit energy falls.

\[
\text{LCOE} = \frac{(\text{Capex} \times \text{FCR}) + \text{Opex}}{\text{AEP}} \tag{3}
\]

FCR is the annual fixed charge rate, which converts the investment lump-sum into an annual payment (e.g. debt repayment) [66]. The discount rate (\( r \)) and the project's economic lifetime (\( t \), years) are used to calculate the FCR as seen in Equation (4) [62]:

\[
\text{FCR} = \frac{r \times (1 + r)^t}{(1 + r)^t - 1} \tag{4}
\]

2.3.2. Revenue predictability and risk

Electricity markets are naturally monopolistic, making it difficult to establish new generating competition when large, capital-intensive investments must be recouped with income streams based on uncertain outputs [11]. Risk increases the cost of capital and the LCOE [15]. Mechanisms to minimise output variability exist but are either not cost effective (large scale storage) or not sufficiently tested (optimum arrays and aggregation) [67].

It is important to understand the complex nature of a site's wind profile. A turbine's rated power is a function of design and should be best suited to the location, improving its cost effectiveness [68]. When the cost of generating remains constant, reducing LCOEs means increasing the energy production from the same assets. From an investment perspective, maximising output by 'sweating' more value out of stranded assets can reduce the risk of not servicing initial investment costs which are a large barrier to low carbon infrastructure developments [9].

3. Assessing LCOE change: a framework

Coupling the outputs from a climate model with wind farm output and financial models can provide the basis for assessing the impact of climate change on the LCOE of wind. This is made possible using software including a statistical package (R) and geographic information system software (ESRI ArcGIS).

3.1. Wind speed resource assessment

The National Oceanic and Atmospheric Association: Geophysical Fluids Dynamics Laboratory – Earth System Model 2 (ESM2G) was chosen from the Coupled Model Intercomparison Project Phase 5 (CMIP5) data, due to relatively high temporal resolution and ease of availability in a standardised online database [38]. The model is based on previous NOAA GFDL models (CM2), using their land component with updated atmospheric and oceanic components; further detail can be found in Refs. [60,69]. Data from CMIP5 was chosen for its scientific rigour, having served as the basis for the IPCC fifth assessment report (AR5). Only three of the RCP scenarios were used, as the ESM2G data for RCP 4.5 are incomplete [70].

Wind speed data from the model runs were acquired in NetCDF format, which provided three-hourly wind speeds at 10 m above ground level, on a regular grid of 2.0° latitude by 2.5° longitude. A twenty-year period (1981–2000) was extracted from the model’s full historic time series (1860–2006) for validation against the NASA MERRA reanalysis.

3.1.1. Power law extrapolation

As ESM2G’s wind speed data are projected at heights of 10 m above ground, they must be extrapolated to the hub height of modern turbines (typically 60–100 m). Wind speeds within the boundary layer are directly proportional to height from the earth’s surface due to friction caused by the surface roughness (applicable up to 100–150 m) [71]. This study uses the power law for its simplicity to extrapolate to a height of 80 m [72,73]. Speed at hub height, \( v(z_h) \), is defined as:

\[
v(z_h) = v(z_0) \left( \frac{z_h}{z_0} \right)^{\alpha} \tag{5}
\]

Where \( v(z) \) is wind speed at height \( z \) and \( \alpha \) denotes the shear coefficient, or Hellman parameter [72]. The shear coefficient is a function of surface topology and varies due to land cover, with values of 1/7 used for onshore and 1/9 for offshore locations [71], assigned using GIS. With additional data on land type, the more complex logarithm wind profile law (among others) could be implemented [63].

3.1.2. Calculation of Weibull parameters

Climate model data files are relatively large, around 28 GB for each future RCP scenario. To reduce the data storage and processing requirements, a Weibull distribution (Equation (6)) can be fitted to wind speed time series data, and then transposed into wind power equations [64].

\[
f(v) = \frac{k}{\lambda} \left( \frac{v}{\lambda} \right)^{k-1} \exp \left( -\left( \frac{v}{\lambda} \right)^k \right) \tag{6}
\]
The resulting distribution of wind speed, \( f(v) \), is described by the Weibull shape \((k)\) and scale \((C)\) parameters, which determine the relative proportion of low and high speeds, and the overall average. Several methods exist to find these parameters \([74]\), with Chang \([64]\) finding that one of the most applicable and reliable is the moment likelihood method which can perform better than other methods of parameterisation in a general context. The shape and scale parameters are calculated from the sum of the individual wind speeds, \( v_i \) \((i = 1 \ldots n)\) using Equations (7) and (8):

\[
k = \left[ \frac{\sum v_i^k \ln(v_i) - \sum \ln(v_i)}{\sum \ln(v_i)} \right]^{-1}
\]

\[
C = \frac{1}{n} \sum v_i
\]

### 3.1.3. Analysis of future wind energy resources

Each RCP scenario’s complete time series (95 years) is compared with the historic. The future projection run covers 95 years (2006–2100), giving 277,400 speed data points per location. This is sufficient to give a statistical foundation to the calculation and parameterisation of Weibull factors and their distributions \([64]\). Slicing the time series into three 20-year periods (2011–2030; 2041–2060; and 2071–2090) enables the analysis period to correspond with a turbine’s lifetime; this gives greater insight to how wind resources evolve over time when looking at the three in sequence \([31]\).

Any potential change in the wind resource distributions can be statistically tested using a Kolmogorov-Smirnov (K-S) test to compare the skew of the wind speed distributions, inferring whether they can be considered to emanate from the same continuous distribution \([4]\). The significance of the change in mean wind speed is tested using a student \( t \)-test; the null hypothesis assumes there is no change due to climate forcing.

The percentage changes in \( \bar{v}_{\text{annual}} \) and \( \bar{v}_{\text{seasonal}} \) from the historic to each projection time frame are then calculated. An \( f \)-test is used to show statistical significance of the differences between projected and historic wind speed patterns; the null hypothesis assumes there is no change due to climate forcing.

### 3.2. Model correction

Climate models exhibit systematic errors in their absolute outputs, such as temperature or precipitation estimates \([75,76]\). As climate models are not specifically designed for projecting wind resources it should be expected that bias correction would be required in this field, especially as modelled speeds are sensitive to the spatial resolution of a model.

As interest typically lies with the relative change from present day to future it is standard practice to use three available data sets (historic and future climate model, and historic observations) to give a best estimate of future observations. The impact of radiative forcing can be estimated from the climate model and then applied to the historic observations, following the horizontal arrows in Fig. 2 (1 then 2). Alternatively, statistical methods for bias correction can be used to bring the model outputs into line with historic observations, and then be applied to the future model runs, following the vertical arrows (A then B).

This correction relies on the assumption that model bias is time-invariant, and thus the transfer function used to correct historic output is applicable in the future. This process has the potential to change the climate signal (the difference between present and future output) if the transfer function is non-linear or has a gradient other than 1 \([77,78]\).

This method cannot remove all bias from the model. For example, if a model incorrectly simulates an atmospheric mechanism like the general trend in storm tracks, any change to this feature of storm tracks will manifest on an incorrect initial frame of reference. An approach to better appreciate and account for this uncorrected limitation is the use of ensemble datasets which compile data from various GCMs and perform analysis on the whole range of input data \([14]\); which this proposed framework is designed to incorporate.

### 3.2.1. Historic validation

A regression analysis can compare the spatial distribution of long-term mean wind speeds. In this study, we compare the ESM2G model historical run (1981–2000) against the MERRA reanalysis Fig. 3.
described in 2.2.2 [79]. MERRA has a higher spatial resolution of 0.66 × 0.5° cf. 2.5 × 2°, as shown in Fig. 3, so its data were upscaled to give average values for each box on ESM2G’s coarser grid.

3.2.2. Weibull transfer function
Several methods of bias correction are employed, ranging in complexity from additive and linear scale factors to quantile mapping [77,78]. In this study, we apply linear transforms to the shape and scale parameters of the Weibull distributions fitted to each wind speed time-series. For the scale parameter this is equivalent to a linear change in wind speeds, while a linear transform to the shape parameter will alter the underlying quantile distribution and thus change the climate signal.

Equation (9) gives the transform that is applied to the Weibull scale parameter (C), based on the historic and future results from the ESM2G model, and the historic results from MERRA which are taken to be the ‘actual’ data. The same transform is applied to the shape parameter (replacing C with k in Equation (9)).

\[
C_{\text{future}}^{\text{MERRA}} = C_{\text{historic}}^{\text{MERRA}} \times \frac{C_{\text{future}}^{\text{ESM2G}}}{C_{\text{historic}}^{\text{ESM2G}}}
\]

Fig. 4 Demonstrates this transformation with an example set of wind speed data. The shift from the solid to dotted lines represents the climate signal (the difference between future and historic), while the shift from the light to the dark coloured lines represents the model correction (the difference between GCM and reanalysis).

3.3. Annual energy production and capacity factor calculation

The power that can be extracted by a wind turbine, \( P(v) \), can be calculated from first principles from air density (\( \rho \), kg m\(^{-3}\)), the swept area of the turbine’s blades (\( A \), m\(^2\)) and the wind speed (v, m s\(^{-1}\)):

\[
P(v) = \frac{1}{2} \rho A v^3
\]

However, the efficiency that a wind turbine can capture this power is a non-parametric function of wind speed which varies from turbine to turbine. It is common to use the power curves which are specified by manufacturers to convert wind speed into power output, for example those which are collated in Ref. [80]. These curves can be scaled to account for real-world effects such as turbulence and masking (nearby objects and structures reducing wind speeds), and smoothed to account for there being multiple individual turbines within a farm, each of which experiences different wind speeds.

Fig. 5 shows a typical manufacturer’s power curve and the corresponding modified ‘farm curve’. The farm curve is shifted to the right, suggesting that wind speeds are 2 m s\(^{-1}\) slower at the nacelles of a real wind farm than is predicted by the weather data [21], and it is smoothed using a Guassian kernel with \( \sigma = 1.5 \) m s\(^{-1}\) according to [81].

This technique applied to either measured wind speeds or reanalysis data has been found to give very good correlation with historic power outputs from wind farms [21,54,55,58], implying that both the reanalysis data source and the calculation method are valid.

When using Weibull distributions to represent wind speed time series, the AEP can be calculated using the sum-product of the Weibull PDF (the fraction of time that wind speeds are at a given level) with the wind farm power curve (which gives the power output for that given speed). As the power curve is non-parametric, this is most easily done as a discrete sum, evaluated at the speeds for which the power curve is defined.

3.4. Levelised cost of electricity (LCOE) calculation

When working with LCOE, it is important to realise that specific prices for individual existing or planned wind farms are difficult to obtain due to commercial sensitivities. The literature has approximations for the LCOE of existing wind farms; the main cost components are summarised in Table 3, with the associated parameters that affect these costs, and how the relative value of each is dependent on the variables addressed in this study.

The main components of capex vary in their relative proportion of costs [62]. Onshore costs include costs associated with roads, leasing land, and soil characteristics [82]. Offshore is dominated by foundation and electrical infrastructure costs which make up larger proportions of total capex the deeper and further from the coast the turbine is [83]. In any case, environmental and socioeconomic
factors can push up prices.

Wind farm costs are almost all fixed, depending on the MW of capacity installed and not varying with the MWh of energy generated. Some fixed costs relate to the physical equipment and will be incurred wherever it is sited, including the turbines, connection to the grid and other technical aspects [15,82]. Some elements of these costs can change over time as they are exposed to price volatility in markets, including currency exchanges, global steel prices, shipping and transportation prices (in particular for offshore), interest and discount rates [62]. Site specific costs are dependent on environmental and socio-economic factors, including distance from infrastructure, land height or sea depth, and the price of land.

In this study, capex and opex are calculated on a site-specific basis and are then assumed to remain constant over time, as the key parameter being considered is wind speed, which will not influence these costs. All other variables which could affect cost, such as the model and height of turbine or the level of service contract, are assumed to remain constant in this study so that results across the country are easily comparable. We base our calculations on a Vestas V122 3 MW turbine at 80 m hub height with an industry-average maintenance contract. The cost of a turbine is dependent on design and specification as well as approximations of variable external factors: currency exchange, discount rates, steel prices, etc. [82].

Onshore turbines have a cost in the range of £0.8—1.0 million per MW [15,84], whereas offshore turbines cost approximately £1.5—1.9 million per MW [62,83]. Offshore costs are due to the increased difficulty in manufacturing, transporting and erecting turbines [85,86]. Based on these sources, the parameters given in Table 4 are used in the calculation of the LCOE.

The high cost of investing in new infrastructure means site selection is an important trade-off between access to existing infrastructure (reducing capex) and higher capacity factors (increasing AEP); both contribute to a lower LCOE [84].

3.4.1. Spatially dependent costs

Although opex and capex remain constant over time; they are spatially dependent. To ascertain costs, simple linear models of a wind farms capex can be developed from the regression of past costs. The key factor in this model for onshore farms is the distance to relevant infrastructure (grid connection and roads). For offshore farms the depth of water for foundation costs and the distance to shore for grid connection costs are key factors; this is governed by the depth being a key component for foundation costs. There is a complex relationship accounting for the applicability of different foundation technologies (e.g. monopiles have a theoretical maximum depth of only 60 m) which has been reduced to a simple linear relationship and applied over all depths in the EEZ [88]. This is a key limitation of this model as sea depth exceeds 4000 m in places, and so with more data, advanced techniques could be used to represent this in more detail [12]. The relationships used to calculate the capex (per MW) for onshore and offshore turbines are given in Equations (11) and (12), using the parameters from Table 4.

\[
\text{Capex}_{\text{onshore}} = \text{Turbine}_{\text{onshore}} + \text{Foundation}_{\text{onshore}} + \text{Grid}_{\text{onshore}} + \text{Balance}_{\text{onshore}}
\]

\[
\text{Grid cost}_{\text{onshore}} = \text{Grid cost}_{\text{onshore Transmission}} + \text{Grid cost}_{\text{onshore Roads}}
\]

\[
\text{Grid cost}_{\text{onshore Transmission}} = \text{distance from grid (in km)} \times £10,900
\]

\[
\text{Grid cost}_{\text{onshore Roads}} = \text{distance from roads (in km)} \times £1,100
\]

\[
\text{Capex}_{\text{offshore}} = \text{Turbine}_{\text{offshore}} + \text{Foundation}_{\text{offshore}} + \text{Grid}_{\text{offshore}} + \text{Balance}_{\text{offshore}}
\]

\[
\text{Foundation cost}_{\text{offshore}} = a + b \times \text{depth (in m)}
\]

\[
\text{if depth < 30 metres} : \ a = £363,000; \ b = £9,800;
\]

\[
\text{if depth ≥ 30 metres} : \ a = £282,666; \ b = £12,700;
\]

\[
\text{Grid cost}_{\text{offshore}} = £785,714 + £2,857 \times \text{distance to shore(in km)}
\]
3.4.3. GIS and spatial interpolation

GIS software is used to create a spatial model of associated levelised productions costs. Ordinary Kriging with a spherical variogram is an interpolation method applied to wind speed data and energy within ArcMAP [91]. Interpolating the point data provides a homogeneous data density over the study area enabling continuous spatial analysis.

As with wind speeds, a continuous spatial function for turbine capex can be calculated. For every grid point, the relevant data from infrastructure and sea depth can be calculated in ArcGIS software using infrastructure data from National Grid [92].

3.5. Framework limitations and extensions

Climate prediction is an inherently uncertain process. It is common practice to test the robustness of a finding by testing multiple climate models and multiple parameter sets (ensemble datasets [37,93]). We demonstrate the results from only a single model, as the focus of this paper is on developing the underlying framework. It is common to also employ downscaling to increase the spatial resolution of the climate model data to gain a better understanding of localised impacts. This paper considers a broad overview of the UK’s wind resources and so downscaling has not been performed.

Calculations involving interpolation invoke high levels of uncertainty. Wind speed and energy are dynamic, complex and chaotic variables which depend on many un-factored parameters. Orography, air pressure and temperature, among others, impact wind resources and have not been accounted for when interpolating spatially or extrapolating up to hub height. A mathematical relationship between proximate data points was used as it is adequate for these preliminary applications.

Further limitations exist when calculating any LCOE which include inter-generational costs and learning curves, currency fluctuations, steel prices, environmental and social costs, and utilisation of specific discount rates. The LCOE model presented in this research is reductive by intention as complex investigations of the metrics being considered (e.g. by comparing the interannual variability or reviewing storm track processes) to improve confidence that the climate signal is being correctly represented.

4) Creating a more detailed LCOE model by incorporating learning curves, greater technological granularity (such as additional types of offshore turbine foundations or transmission cables), and time-varying O&M costs.

4. LCOE change in the UK: example application

This section presents an exemplary application of the framework with the ESM2G data as outlined in Section 3. Projections of the UK’s wind energy resource under RCP scenarios through to 2100 are used to demonstrate the relevance of this framework in the context of current UK wind energy policy.

This section looks at the validation of framework inputs (LCOE and climate model simulations), the change in wind resource distributions, and finally the impact this has on the AEP, CF and LCOE.

4.1. Model validation

4.1.1. Spatial LCOE simulation

The present-day LCOE was estimated using the financial parameters from Section 3.4 and the historic wind speed data from MERRA. The spatial variation in LCOE is presented in Fig. 6, and is compared to literature estimates and historic outturn in Fig. 7. Onshore, LCOE ranges from the mid 40 €/MWh in Scotland to the mid 90 €/MWh in England and Wales; while offshore, Thames Estuary estimates are approximately £120 MW h⁻¹ and Dogger Bank is in the region of £150 MW h⁻¹. The simulated LCOE (Fig. 7) corresponds well with the literature’s existing projections on and offshore [17]. The validation of the LCOE model does a poorer job with where the reference LCOE values from DECC contract for Difference (CID) strike prices [94]. The LCOE model overestimates both East Anglia One and Neart na Gaoithe sites on average by 38%, whereas the majority of both onshore and the other offshore Round 2 and 3 sites are simulated to within ±13%. DECC’s method of calculation is different to the method that has been employed in this research [17]. Shallower coastal areas exhibit adequate LCOE simulation [17,93,96].

4.1.2. ESM2G wind speed simulation

The average level of wind resource simulated from the ESM2G historic run shows poor agreement with the MERRA reanalysis as shown in Fig. 8. The error shows marked differences across a relatively small geographic area, with overestimated resources in the south east and underestimated the north west of the UK.

Reasons for the difference between simulation (ESM2G) and the best estimate of reality (MERRA) are inherent to model design, code

Table 4

<table>
<thead>
<tr>
<th>Component/input parameter</th>
<th>Onshore value</th>
<th>Offshore value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Turbine and tower (including installation)</td>
<td>£1,000,000 M W⁻¹ [15]</td>
<td>£1,500,000 M W⁻¹ [59]</td>
</tr>
<tr>
<td>Foundations</td>
<td>£80,000 M W⁻¹</td>
<td>Function of depth [80]</td>
</tr>
<tr>
<td>Electrical infrastructure</td>
<td>Function of distance from grid and roads [15,82]</td>
<td>Function of distance from shore [87]</td>
</tr>
<tr>
<td>Balance of system</td>
<td>4% of capex</td>
<td>7% of capex</td>
</tr>
<tr>
<td>O&amp;M</td>
<td>5% of capex [59]</td>
<td></td>
</tr>
<tr>
<td>Turbine lifetime</td>
<td>20 years</td>
<td></td>
</tr>
<tr>
<td>Discount rate</td>
<td>7.5% [15]</td>
<td></td>
</tr>
</tbody>
</table>

*See below for specific functions (Equations (11) and (12)).
and purpose. ESM2G has been designed to investigate ocean circulation, not primarily for the use of wind resource analysis [60]. It should also be noted that the lower spatial and temporal resolution of the GCM output reduces the heterogeneity of these dimensions; the results should be considered within this context.

4.2. Change in wind resource (before transfer function)

4.2.1. Average wind speeds

A series of Student’s T-Tests, F-Tests and K-S Tests investigated the significance of the differences between historic and projected mean wind speeds, mean variance and cumulative distribution functions respectively. They showed that a number of time periods and RCPs had a significant change in wind resources in some parts of the study area.

The model’s 2.6, 6.0 and 8.5 RCP future projection scenarios agree with a general pattern of change when compared to the historic run: the North Atlantic and North Scotland tends to have the greatest increase in wind resource change whilst South England and the English Channel have the greatest decrease in wind resource. When comparing the RCPs with each other, it is possible to identify two key trends: the greater the radiative forcing, the greater the relative magnitude of change occurred; the climate signals are more pronounced later in the time series relative to earlier periods. Mean annual wind speed increases most in the north, this signal is stronger in RCP 8.5 whilst it is weakest for RCP 2.6; the same is true for the decrease in mean annual wind speed in
the south of the study area.; RCP 6.0 projects the strongest decrease over the south of England.

4.2.2. Interannual and interseasonal variability

As shown in Fig. 9, the magnitude or direction of the IV_{annual} change is non-linear with time. The IV_{annual} between the time periods shows either decreases in the IV_{annual} in the North West of the EEZ, or at best a small increase; contrasting the South and East of the EEZ has the largest increases in the IV_{annual}. Much like the IV_{annual}, IV_{seasonal} of the wind resource is also projected to change, as shown in Fig. 10. The results show that the seasonal variability increases over much of the land; the greatest loss of IV_{seasonal} is in the extreme north and south of the study area, corresponding to areas of greatest relative climate impact; autumn has the greatest loss of variability; and spring becomes relatively more variable. The seasonal trends are also quite concurrent between the RCP scenarios; spring generally increasing in wind speed whilst autumn decreases in mean wind speed.

4.3. Change in energy output and LCOE (with transfer function)

The CF and AEP follow the trends outlined with the wind resources in Section 4.2 due to their monotonic relationship with wind resource. Fig. 11 shows that the open sea off the north and North West of Scotland gain the most in terms of AEP and CF; whereas the waters off the south and south west of England have a reduction in those parameters. This results in proportionally lower and higher LCOEs for the regions respectively, as shown in Fig. 12.

The greatest reductions of LCOE are in Scotland and North Atlantic (>1% decrease in cost). Contrastingly, increases in LCOE are confined to the south English coast, with the greatest increases off the South West Cornish coast (>1% increase in cost). The main difference between the RCP scenarios is the ‘peak’ in LCOE increase is found earlier within the RCP 2.6 time series whereas in the other RCPs (6.0 and 8.5) the intensity of the LCOE increase occurs in the later stages of the century (2071–2090).

5. Framework findings

5.1. Are wind resources projected to change?

The UK wind resource undergoes a non-linear response to increased climate forcing. In places these can be considered statistically significant, and climate signals tend to be larger with greater climate forcings (RCP 6.0 and 8.5 [34]). The model outputs show resource changes in their distributions and central tendencies under different time periods and radiative forcings. Although the model reaffirms that climate change can impact the wind resource distributions [statistically] significantly over the space of a few decades, it is unlikely to cause a drastic change in the mean wind speeds will impact annual wind energy output [24].

In the wider context of existing research, ESM2G concurs with other model projections; mean wind speeds expected to increase over the north (particularly in winter) and decrease in the south (particularly in summer) following the strong seasonal signal [24]. There is some discordance in the results, for instance ESM2G projects significant decreases in autumn winds whilst the wider literature projects the opposite to be the case [31,97]. It becomes clear that using multiple model and ensemble runs of outputs has its benefits in reproducing a suite of plausible scenarios of future wind resources in addition to downscaling methods that attempt to capture greater spatial variation [14].

If the projections become manifest, then we could find increasing energy potentials in Scotland and Northern England: particularly attractive for investment in increased electricity.
transmission interconnections between Norway and Great Britain. This is just one possible outcome of climate change, not the ‘expected’ case amongst the climate science community [31].

5.2. Model historic performance

The findings show that ESM2G poorly represents the current and historic spatial distribution of the UK’s wind resource, which could be expected as this was not the model’s stated purpose. It is important to note that the projected changes in wind speeds and their distribution are underpinned by the assumption that the physical processes which generate these winds remain unchanged in the future scenarios influenced by climate change.

There are complex reasons behind this including inherent

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Fig. 9. Change in interannual variability during (a) 2011–2030, (b) 2041–2060, (c) 2071–2090, and (large) historic.
uncertainty associated with all climate models, differences in design, scenario conditioning, the model’s spatial resolution being too coarse to represent the fundamental processes governing wind speeds, and statistical analysis employed (Weibull, aggregation and interpolation). The last point is particularly resonant due to the different disciplinary scopes that frame outputs according to convention within their fields [33,38,98]. It may follow that ESM2G also incorrectly represents the climate signal relating to wind speeds; hence work could be directed towards validation of these results, particularly through a comparison between climate models and ensembles.

There is also potential for GCMs to better consider wind speeds.
as an output. This should include a more detailed treatment of the atmospheric processes which generate winds, providing data that is more relevant for energy calculations (such as wind speeds at 50–100 m above ground) and increasing the horizontal (spatial) resolution (e.g. 1° or less).

5.3. Wider context of the results

5.3.1. Impacts on current UK energy policy

With a privatised yet regulated electricity market, the main generators are largely bounded by government policy. This is even
more so the case with wind farm as they still largely depend on government subsidy to, at best, smooth out their income stream via financial instruments tailored to incentivise low carbon capacity [94].

The data and analysis presented here shows a 0.9% increase in average annual capacity factor for the Dogger Bank (RCP 6.0, 2011–2030). This equates to an additional 44 MWh per year from each 3 MW turbine. If the offshore strike price is agreed at a constant £120 MW h$^{-1}$ [95], this will benefit the developer (and cost the tax payer) an extra £5000 a year (or £100,000 over 20 years) from allowing the wind to take its course. This can significantly impact the Climate Control Levy if capacity factors increase, or even decrease, especially due to the clustering of wind farms in certain regions [99]. Long term studies may be used to effectively site wind farms to increase the chances of securing a higher subsidy from government via rent seeking or mitigate this risk [21].

As the time horizons for different scales of infrastructure change, it may be in the transmission system operator’s best interest to focus on investments where the lowest risk to increasing costs are placed. In this context picking a winner in terms of large infrastructural projects is the case.

5.3.2. Investment opportunities

Coupling climate model outputs to a multi-criteria decision models (MCDM) of turbines and associated costs could provide an extra commercial advantage [24]. Allowing the model to indicate when a wind turbine is no longer suitable for that area based on changing wind profiles could be used to provide some foretaste into how attractive a site may become for long-term sustainable asset and infrastructure management. Procurement of appropriate machinery and supply chain reinforcements can allow a nation’s ageing electricity and energy infrastructure to adapt to changing renewable resource availability; however this requires a coordinated and planned approach to future investments.

Models increasingly form a cornerstone for future analysis into resource dynamics. This framework can be used to assist in prioritising long term infrastructural investment; approximate costs; provide foresight; and reduce uncertainties and risks associated with climate change.

5.4. Interdisciplinary nature of research

The numerous stakeholders involved with wind power generation, research and investment are highly variable in their capabilities to work cohesively across the requisite disciplines. The diverse fields of expertise make it challenging to streamline due to different conventions in data processing, analysis and research interests. Large amounts of data processing are not conducive to non-quantitative interaction. However, increasing numbers of researchers are working holistically to investigate the same questions. It induces discourse as to what the role of climate science is in modelling future variables. Attaching costs implicitly attaches subjective value; political interest to secure greater echelons of certainty, regardless of whether projected future trends have primarily been to infer understanding and not form the evidence basis for political (in) action.

6. Conclusions

In accordance with the first aim of this paper, a framework for investigating such dynamics in wind resources due to climate change has been created. This links together meteorology, engineering, economics and policy together and allows the outputs from one discipline to be translated into the language and metrics of others. The framework we present is generic and adaptable, it can be applied to other climate models (or preferably ensembles of
models), to other world regions, and could even be applied to other renewable technologies such as solar, hydro or marine.

Meeting the second aim, the framework was employed to investigate the future of the UK’s wind resources and industry. This was meant as an exemplary demonstration not a comprehensive analysis, hence only one climate model was used, and it was chosen based on convenience and accessibility, rather than a rigorous assessment of quality. Although the results are based on poorly validated data, considered statistically insignificant, the selection of model output was driven by maintaining high quality data in terms of temporal coverage. These data requirements which are conventional for energy analysts are not typically what climate models produce as output. This contextualises the framework of climate modelling as not being a panacea to complete comprehension of risks in the natural world, be they natural or anthropogenic [100]; it does highlight the potential for coupling environmental and socioeconomic models to greater extents and importantly improves our understanding of the earth system.

The LCOE model shows that climate change impacts wind resources and LCOEs both temporally and spatially. The ability for model projections to perfectly simulate historical baselines should not act as a barrier to research; constructing frameworks allows greater understanding when better suited data arises. Multiple factors are considered, including: complementary research; differences between data conventions; uncertainty and its translation into risk pose a series of hurdles to completing research. Significantly, the largest barrier to high wind energy development in the UK is uncertainty; the largest sources of uncertainty arise not from resource analysis but from political motivation. Government policy becomes the start and end aspect of an iterative cycle, whilst the wind energy as a proportion of UK electricity is expanding [101].

This research focuses on the energy production aspect of the LCOE equation, within the coming decades the wind power industry may continue to experience learning curves and reduce costs by optimising manufacturing and deployment of wind turbines [102]. Costs of turbines are expected to change, and the sensitivity of LCOE to the discount rate are also important. In this study a 7.5% discount rate was used based on the literature; however private investors may apply higher rates depending on their outlook. The change in the cost of infrastructure and capital are far higher than any currently conceivable change in energy output [151],62. Financial ramifications of ever changing policy (which is more dynamic that the wind itself) can create volatility in confidence – strike prices and EMR pose an interesting scenario for future observations of fluctuating LCOEs.

Policy makers have tactile influence on the cost of capex and opex of wind turbines, more so than they can impact the wind speed or AEP of turbines. The real crux when it comes to reducing the cost of wind power is not only by better site selection to improve capacity factors, the laws of physics determine that, but political motivation is too. The laws of political and economic convention are in the eyes of the beholder and are fundamentally a lot easier to subjectively change than the objectively impossible.

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