Climate Change and Renewable Energy Portfolios

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Abstract

The UK has a commitment to reduce greenhouse gases by at least 80% from 1990 levels by 2050. This will see the proportion of energy generated in the UK from renewable resources such as wind, solar, marine and bio-fuels is increasing and likely to dominate the future energy market over the next few decades. However, it is unclear what effect future physical climate changes could have on the long term average energy output characteristics of individual renewable energy technologies that may dominate the low carbon energy technologies. It is also unclear how these changes to individual technologies will affect a diverse portfolio of electricity generation technologies.

This thesis explores the influence of climate change on renewable electricity generation portfolios and energy security in the UK, with the aim of determining if climate change will affect renewable energy resource in such a way that may leave future low carbon generation portfolios sub-optimal. The research allows long term renewable resource variability to be reflected within models of the costs and risks associated with different electricity generation technologies and using Mean Variance Portfolio Theory (MVPT), it explores the influence of climate change on renewable energy portfolios and energy security in the UK.

The scope of this study has a considerable range spanning from renewable resources through to the sensitivity of an optimal portfolio mix of generation technologies to climate change. In brief, the objectives were as follows: Characterise the variability of renewable energy resources and electricity generation output from renewable technology in the UK, in particular solar PV, on and offshore wind, for future climate scenarios for the 2050s and 2080s. Characterise the variability of electricity generation costs and explore the effect of climate change scenarios on generation costs and risk by examining the cost-risk balance of current and potential future low carbon electricity generation technology portfolios.

The outcome saw distinctive changes in solar, wind, wave and hydro resource. The changes were largely negative, except in the case of solar, which increased. Levelised costs decreased for solar PV but increased for the technologies with negative resource changes. Evident changes in optimal portfolio mixes were observed and explored.

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To UK Energy Research Centre (UKERC) for funding me.

And finally, to all my musician friends for providing even more distraction.

Declaration

I declare that this thesis has been written by myself. The research contained within is my own work except where indicated to the contrary. The work has not been submitted for any other degree or professional qualification.

Dougal James Burnett

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Abbreviations

AOGCM	Atmosphere-Ocean General Circulation Model
BADC	British Atmospheric Data Centre
BERR	Department for Business, Enterprise and Regulatory Reform
BWEA	British Wind Energy Association
CAPM	Capital Asset Pricing Model
CO_2	Carbon dioxide
DECC	Department for Energy and Climate Change
DEFRA	Department for Environment, Food and Rural Affairs
DTI	Department of Trade and Industry
ECMWF	European Centre for Medium-range Weather Forecasting
EIA	Energy Information Administration
ERA40	ECMWF 40-year reanalysis project
ETS	Emissions Trading Scheme
GCM	Global Climate Model
GHG	Greenhouse Gas
HADCM3	Hadley Centre’s AOGCM
HadRM3	Hadley Centre Regional Climate Model
IPCC	Intergovernmental Panel on Climate Change
MVPT	Mean Variance Portfolio Theory
MIDAS	Met Office Integrated Data Archive System
NOABL	Numerical Objective Analysis of Boundary Layer
NPV	Net Present Value
O&M	Operations and Maintenance
PV	Photovoltaic
RCM	Regional Climate Model
SRES	Special Report on Emissions Scenarios
TAR	Special Report on Emissions Scenarios
UKCIP	UK Climate Impacts Programme
UKCP09	UK Climate Impacts Programme 2009
UKMO	UK Meteorological Office
UNEP	United Nations Environment Programme
WEC	Wave Energy Convertor
WMO	World Meteorological Organisation

Symbols

σ_p	Expected portfolio risk,
σ_1, σ_2	Risk of each investment
σ_{12}	Correlation coefficient of the historic return between two assets.
ϕ	Latitude (degrees)
δ	Declination of the sun (degrees)
β	Correlation between the expected return of an asset and the expected return of the market.
ρ	Air density (~1.2 kg/m^3)
$	US Dollar
€	Euro
A	Area (m^2)
$E(R_p)$	Expected portfolio return
f_{clear}	Time fraction that no significant clouds block the sun
g	gravity constant
h_{ss}	Sunrise / sunset hour angle on a horizontal surface (degrees)
$\overline{H}_t$	Monthly average of daily radiation on the tilted surface (J m^{-2})
$\overline{H}_{bt}$	Direct radiation on a tilted surface
$\overline{H}_{dt}$	Diffuse radiation on a tilted surface
$\overline{H}_{rt}$	Ground reflected radiation on the tilted surface
$\overline{H}_d$	Monthly average of daily diffuse horizontal surface radiation (J m^{-2})
$\overline{H}_t$	Monthly average of daily radiation on the tilted surface (J m^{-2})
$\overline{H}_{clear}$	Monthly average of daily horizontal surface clear sky radiation (J m^{-2})
$\overline{H}_o$	Monthly average of daily horizontal extra-terrestrial radiation (J m^{-2})
I_{sc}	Solar constant = 1367 W/m^2
I_o	Extra-terrestrial solar radiation at normal incidence (W/m^2)
$\overline{K}$	Monthly average daily clearness index
$\overline{K}_{clear}$	Monthly average clear sky clearness index.

kW	kilowatt
LCOE	Levelised cost of electricity
LC_D	Discounted levelised cost
MW	Megawatt
MWh	Megawatt-hour
n	Day of year starting at 1st January
n	Number of samples
N	Day length (hours)
PV	present value
PV	Photovoltaic
r	discount rate
$\bar{r}_b$	Monthly average daily direct radiation conversion factor
$\bar{r}_d$	Monthly average daily diffuse radiation conversion factor
$\bar{r}_r$	Monthly average daily ground reflected conversion factor
R_i	Expected return of an asset
R_f	Risk free rate of return
R_m	Expected return of the market
s	Sample standard deviation
$SE_{\bar{x}}$	Standard error of the mean
t_α	T-value of the t-distribution
TW	Terrawatt
TWh	Terrawatt-hour
U	Wind speed (m/s)
$U_{19.5}$	average wind speed at 19.5 m above sea level
$\overline{U}$	Average wind speed (m/s)
$v(z)$	Wind speed at height z (m/s)
$v(z_r)$	Wind speed at the reference height (m/s)
$\overline{X}$	Sample mean
X_1, X_2	Proportions of each investment
z_o	Surface roughness length (m)

1 Introduction

1.1 Context

The UK has a commitment to reduce greenhouse gases by at least 80% from 1990 levels by 2050 (DECC 2008). The proportion of energy generated in the UK from renewable resources such as wind, solar, marine and bio-fuels is increasing and likely to dominate the future energy market over the next few decades if government support continues. However, it is unclear what effect future physical climate changes could have on the long term average energy output characteristics of individual renewable energy technologies that may dominate the low carbon energy technologies.

It is widely accepted that a diverse electricity generation mix of technologies contributes to security of supply (Awerbuch *et al.* 2003, Bazilian *et al.* 2008, Grubb *et al.* 2006, Skea 2010). There is much interest from academics, policy makers and other interested parties in capitalising as much as possible on the benefits of the diversity in electricity generation technologies. Mean Variance Portfolio Theory (MVPT) is a financial based approach that is receiving growing interest in identifying optimal electricity generation mixes. To date, much of the interest has been to investigate how renewables, which are often more costly than traditional fossil fuelled technologies, can lower financial risk and lower overall costs when part of a diversified electricity generation mix (Awerbuch *et al.* 2003, Awerbuch 2005a, 2005b). MVPT can be effectively used to investigate the costs and risks of a mix of several electricity generation technologies together as a portfolio and in doing so identify optimal electricity generation technology mixes.

However, studies of MVPT and the identification of optimal portfolio energy mixes for the present and future are based on the present (baseline) climate. It is unclear how portfolios of energy mixes that are designed (or selected) based on the resource characteristics of the present climate will be affected by the renewable resource characteristics in a future climate.

1.2 Hypothesis, Objectives and Scope

This work aims to answer the following hypothesis that:

> *Physical climate change will affect renewable energy resources in such a way that its impact may be likely to leave future optimal UK electricity generation portfolios sub-optimal.*

The scope of this study has a considerable range spanning from renewable resource in the UK through to the sensitivity of an optimal portfolio mix of renewable electricity generation technologies to climate change. The objectives are summarised below:

- Investigate renewable energy resource in the UK, in particular solar and onshore and offshore wind resource for the baseline (1961-1990) climate.
- Explore the potential future mid to long term (2011 to 2080s) UK technology deployment of solar PV and on and offshore wind farms and estimate the potential baseline electricity generation output of the technologies deployed.
- Characterise the variability of renewable energy resources and electricity generation output from renewable technology in the UK, in particular solar PV, on and offshore wind, for future climate scenarios for the 2050s and 2080s.
- Characterise the variability of electricity generation costs given the explicit representation of each renewable resource.
- Explore the effect of climate change scenarios on generation costs and risk by examining the cost-risk balance of current and potential future low carbon electricity generation technology portfolios. This will allow the impact of changes in individual generating technologies to be seen in terms of their contribution to future energy supply diversity and security, and optimal portfolios of generating technologies to be determined under current and future climates.
- Assess the extent that the increased variability of renewable resources due to anthropogenic climate change will affect optimal electricity generation portfolios.

1.3 Contribution to Knowledge

The research explores the impact that future climate change may have on optimal electricity generation portfolios. Technology investment decisions are driven by economic assessment and confidence on the part of the investor. Consequently this research will highlight to energy policy makers, researchers, investors, and others engaged in climate change and electricity generation decision making, the additional economic and physical risk that climate change may impose on future electricity generation mixes, specifically those with high proportions of renewables.

While there has been growing use of Mean Variance Portfolio Theory to identify future electricity generation mixes that have optimal cost and risk characteristics (Awerbuch *et al.* 2003, 2005, 2006, 2007; Doherty *et al.* 2006; Grubb *et al.* 2006; Jansen *et al.* 2004; Roques *et al.* 2010) they have all assumed output from renewable technologies based on the characteristics of the current climate. This work shows that such scenarios may be susceptible to significant additional cost and risk which may result in the mix being sub-optimal.

Additionally, geographical UK renewable resource maps have been created for solar and on and offshore wind based on both the present (baseline) climate and projected probabilistic future climates indicated by the UKCP09 scenarios (Murphy *et al.* 2009). The impact on these individual technologies are highlighted and discussed.

Better knowledge on the sensitivity of optimal portfolios and individual technologies to climate variability can be of benefit to renewable energy developers, their financiers, energy policymakers, the academic community and society as a whole.

1.4 Outline

The thesis is organised into 9 chapters with appendices containing additional information. This chapter (Chapter 1) introduces and sets out the objectives, scope, contribution to knowledge and outline of the thesis.

Chapter 2 provides a background to the different fields required to answer the hypothesis. Climate change and projections with emphasis in the probabilistic UK Climate Projections 2009 (UKCP09); renewable technologies and their resource are briefly discussed. Energy economics and Mean Variance Portfolio Theory are introduced and discussed. All these fields are required to meet the aims and objectives of this thesis set out in section 1.2.

Chapter 3 assesses the UK solar resource for the current climate by converting sunlight observations to surface solar irradiation. This is then converted into electricity production from solar photovoltaic (PV) modules. The potential climate change impact on the resource is then investigated using values from the UKCP09 probabilistic projections.

Chapter 4 assesses the onshore wind resource over the UK using gridded observed wind speed data, appropriate wind distributions and wind turbine power curves. Climate change is investigated by analysis of wind speed output from the HadRM3 regional climate model (RCM) which includes future CO_2 emission scenario outputs.

Chapter 5 assesses the offshore wind resource in UK waters using HadRM3 baseline wind speed data, and appropriate distributions. Climate change is investigated in the same manner as performed for onshore wind in Chapter 4.

Chapter 6 investigates and discusses other electricity generation technologies that may be affected by climate change. Section 6.1 investigates the potential sensitivity of wave energy resource due to climate variability by converting baseline and future wind speed data to wave resource using the Pierson Moskowitz spectrum method, then converting the resource at different time periods to wave energy using the power curve of a wave energy converter (WEC). Section 6.2 discusses hydro, which is included in the levelised cost and MVPT analysis using baseline and climate change resource figures from another study (Duncan 2012). The following section discusses tidal, biomass, biofuels and thermal plant and the way they could be affected by climate change are all briefly discussed; however, they are assumed to be unaffected by climate change for this study. Section 6.4 reviews the monthly resource changes for all the technologies covered in this and previous chapters.

Chapter 7 discusses current and future levelised costs for different electricity generation technologies, then calculates and specifies current and future technology and current and future climate levelised costs to be used for the Mean Variance Portfolio Theory analyses.

Chapter 8 presents the Mean Variance Portfolio (MVPT) analysis and explores the sensitivity of different optimal electricity generation mixes to climate variability.

Finally, Chapter 9, provides the thesis outcomes and conclusions, as well as its limitations and future work that could further enhance the investigation of electricity generation portfolios and the potential effect of climate change.

1.5 Thesis Flowchart

Figure 1-1 illustrates the basic flow and work packages of the thesis. The three blocks feeding into the ‘data select’ send current and future climate parameters to the technology ‘resource model’ blocks. The second tier blocks contain the ‘resource model’ and ‘energy yield’ models and are discussed along with the climate parameter output in Chapters 3 to 6 for solar PV, on- and offshore wind, wave and hydro respectively. The climate parameters are processed to create current and future resource and energy models. Energy output values are required by the ‘cost-risk models’ in the third tier blocks. The ‘other technologies’ input parameters are from Mott McDonald (2010). ‘Cost-risk models’ for each of the technologies, discussed in Chapters 7 and 8, are generated using technology cost input parameters and data from the resource models. Finally, in Chapter 8, optimal portfolios for baseline and future climates (in green) are generated and compared using input from the ‘cost-risk models’ and predefined ‘MVPT Input Parameters’. The ‘MVPT Input Parameters’ introduce physical technology constraints and are discussed in Chapter 8. The optimal portfolio blocks are where the future hypothesis, that climate change impact may be likely to leave future planned optimal UK electricity generation portfolios sub-optimal, is tested.

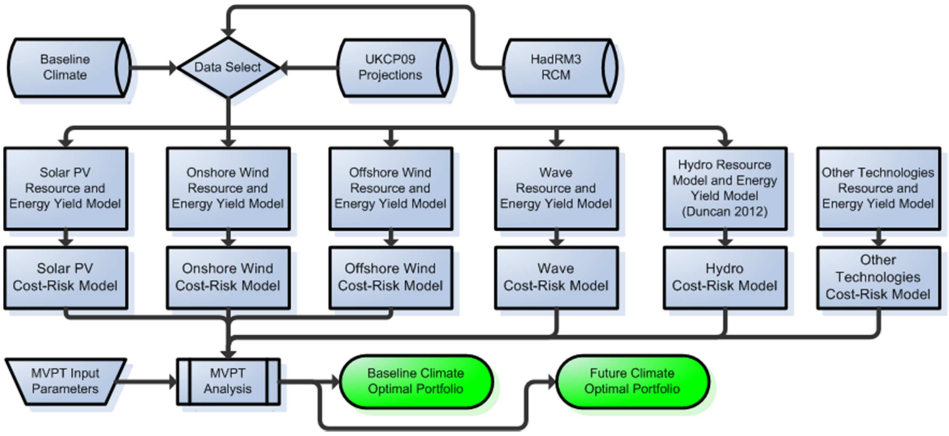


Figure 1-1: Basic Flowchart of Thesis Workflow

2 Thesis Background

The following sections in this chapter are intended to provide the reader with a general background to the main topics of interest covered in this thesis. It covers climate change, renewable energy resource and technologies, electricity generation economics and risk, security of supply, diversity, CO_2 emission reduction and mean variance portfolio theory (MVPT). It is not intended as an exhaustive literature survey of all material, rather it is a targeted effort to equip the reader with sufficient knowledge of essential material.

2.1 Climate Change

Climate change can be defined as any significant change in a normal weather pattern over an extended period of time, typically observed over a period of decades or longer (IPCC 2007). The changes are often expressed in average variability from the present climate and in monthly, seasonal or annual average values. Changes in the climate are mainly due to natural processes but recently there have been escalating changes in the climate and increasing evidence showing these to be due to human activities, most noticeably the increasing level of CO_2 and other greenhouse gases (GHG) being emitted into the atmosphere due to human processes (IPCC 2007). The United Nations Framework Convention on Climate Change (UNFCCC 2012) has a differing definition of climate change. It refers to climate change as being a change in the climate that is directly or indirectly caused by human activity, and that climate change is an additional change to natural climate variability (UNFCCC 2012). ‘Human-induced’ and ‘anthropogenic’ are also popular terms to describe the proportion of change in the climate change due to human activity. This thesis will use the term ‘climate variability’ as a general term to describe the long term average climate change due to human activity, ‘annual average climate variability’ to describe the annual average component of the climate variability and ‘intra-annual climate variability’ to describe the seasonal component of the climate variability.

2.1.1 Intergovernmental Panel on Climate Change

The Intergovernmental Panel on Climate Change (IPCC) was set up in 1988 by the World Meteorological Organisation (WMO) and the United Nations Environment Programme (UNEP) to provide objective scientific assessments and reviews of anthropogenic (human-induced) climate change. The IPCC (2007) supports the view that recent global temperature increases and other recent climate trends, are attributable to the increase of anthropogenic greenhouse gases released into the atmosphere. Global warming is expected to continue while GHG concentrations in the atmosphere escalate (IPCC 2007).

New climate change research and information is continually becoming available from scientists all over the globe, many of who are associated with the IPCC. The most recent information is evaluated and assessed by the IPCC and much of it used in IPCC climate change reports and assessments. The latest report titled ‘Climate Change 2007’ (IPCC 2007) is the fourth in the series and discusses the observed changes in the climate and the effect and causes of the changes. It also investigates the projected future climate changes under different greenhouse gas emission scenarios.

2.1.2 UK Climate Impacts Program

The UK Climate Impacts Programme (UKCIP) was set up by the UK Government to provide climate change information and help the public and private sectors to understand how climate change will affect their organisations and to support them with adapting to these changes. The UKCIP have commissioned several projects funded by DEFRA to create climate change data sets for the UK that are aligned with the IPCC emission scenarios.

The most recent climate change scenarios project carried out jointly by the Hadley Centre and the Tyndall Centre for the UKCIP was named UKCP09 UK Climate Projections and released in 2009 (UKCIP 2009). The UKCP09 project provide future climate projections over UK land and sea locations. The projections are based on the relative change from the 1961-1990 baseline period. In most cases the outputs are given a probability of future climate outcomes for three different future emission scenarios. A normal distribution curve with UKCP09 probability levels (or confidence points) is shown in Figure 2-1. The 10%, 50% and 90% confidence levels describe the probability of change being less than the stated value. The confidence levels described here are used frequently throughout this thesis.

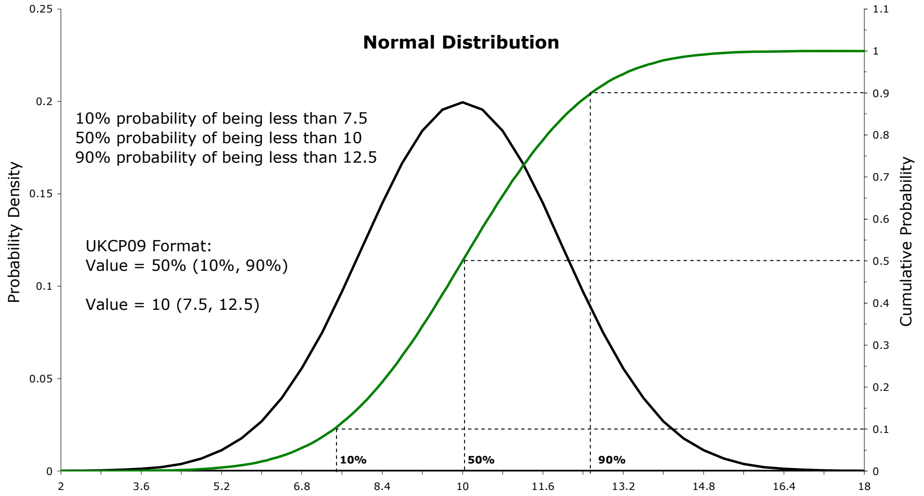


Figure 2-1: Normal distribution with 10%, 50%, and 90% probability levels shown.

The objective of the probabilistic approach in projecting future climate change is to account for the fundamental causes of uncertainties in the future climate and the projections. These are natural climate variability, incomplete understanding of all the Earth processes, modelling uncertainty, and the uncertainty of future GHG emissions (Murphy *et al* 2009). The uncertainties are relatively small leading towards the 2020s, but there are more substantial changes with great divergence through the 2050s and towards the 2100s.

The UKCP09 future time periods include seven 30-year time periods from the “2020s” (represented by 2010 to 2039) to the “2080s” (represented by 2070 to 2099). Three scenarios of future GHG emission scenarios have been modelled (low, medium, high) and are aligned with specific IPCC emission scenarios. The UKCP09 output is only a select set of uncertainty for future scenarios. It is not a complete estimate of uncertainty.

The UKCP09 projections are much improved over previous UKCIP projections such as the UKCIP02 report (UKCIP 2002). The projections are at 25 km resolution providing greater geographic credibility. Modelling and natural climate variability uncertainties are taken into account by the use of probabilistic output and a perturbed physics ensemble (PPE) (DEFRA 2009). This is produced by running a climate model many times with different input parameters with each run being a model variant. Runs from other climate models are also included so as to capture a greater range of outcomes. In this way the variability between different climate models is captured in the probabilistic output. Future emission uncertainty is captured by the use of the three different emission scenarios.

The UKCP09 grid, shown in Figure 2-2, is rotated and has a resolution of 25km^2. There are a total of 434 cells that contain land data over the UK.

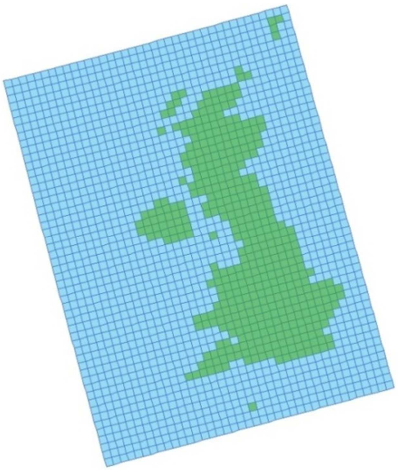


Figure 2-2: UKCP09 Land Projections - 25km^2 resolution grid over the UK

2.1.3 Climate Modelling

Global climate models (GCMs) are complex numerical computer models that use the general principles of fluid dynamics and thermodynamics to model the Earth's climate and all interactions between the atmospheric, ocean, sea ice and land surface processes. GCMs are used to study the impact of increasing levels of greenhouse gases by externally forcing the models with their recent historical and future scenario levels. The IPCC 2007 report contains an extensive chapter discussing climate models and the Atmospheric-Ocean General Circulation Models (AOGCMs) used in the report to estimate future climate change for future emission scenarios (Randall *et al.* 2007). The IPCC has a total of 21 different global climate modelling groups that all contribute towards the IPCC 2007 report. Sets of identical experiments and GHG scenarios are performed on each individual model with the biased outputs reflecting average change and uncertainties in future temperature trends and other climate parameters (IPCC 2007, Wang 2005).

One of the main Regional Climate Models (RCM) used to generate the UKCP09 projections is the Hadley Centre HadRM3 (Met Office 2008), which has grid square spatial resolution of 25km. The HadRM3 model is driven by the Hadley Centre's HadCM3 atmosphere-ocean general circulation model (AOGCM) (Met Office 1999). The HadCM3 model has a spatial resolution of 2.5^o latitude by 3.75^o longitude (roughly 400km by 270km), which is good for climate change predictions on a global scale. To achieve a higher resolution suitable for the UK the scenario outputs from HadCM3 were dynamically downscaled by using the output to drive the HadRM3 model.

The HadCM3 model has also been extensively used by the IPCC. It was used to study the human-induced climate response from the year 1860 to present and then to model the forcing up to the year 2100 for each of the emission scenarios. The model is an updated version of its predecessor HadCM2 with improved atmosphere and ocean components which prevents previous excessive climate drift. It is driven using emission scenarios (A1FI, A2, B2, B1) from the Special Report on Emission Scenarios (SRES) introduced in the IPCC Third Assessment Report (Johns *et al.* 2003).

UKCP09 provides probabilistic projections for many but not all climate parameters. Wind speed is one of the parameters not included in the initial release of UKCP09 because at the time of release there was thought to be too much wind speed uncertainty between the different climate models used in the report (Murphy *et al.* 2009). UKCP09 instead recommended parties interested in wind speed to use projected wind speed output included in the HadRM3 PPE 11-member RCM ensemble (referred to from now as HadRM3). HadRM3 is one of the main data sets used in the UKCP09 report, it consists of output from eleven ensemble runs of the HadRM3 climate model for a medium emissions (SRES1AB) scenario and simulates the UK climate over the period 1950 to 2100 (Met Office 2008).

In November 2010 the UKCP09 added probabilistic wind speed projections to the report after initial integration issues of wind speed from other climate models were resolved (Sexton *et al.* 2010). The projections are not contained in the main user interface and can't be used in conjunction with other probabilistic data but are accessible separately. Unfortunately, the release of this data was too late for direct inclusion in this work.

Climate driven changes in waves is also not included in the UKCP09 probabilistic projections but was investigated and discussed in the UKCP09 Marine Report (Lowe *et al.* 2009).

2.1.4 Climate Change Impact

One of the most obvious ways of speculating future climate change and its impact on energy systems is by the study of historical changes in observed climate parameters. The most evident factor is the observed rise in average air and ocean temperatures. Eleven of the years between 1995 and 2006 were amongst the 12 warmest years in record (since 1850). The average warming trend between 1956 and 2005 (0.13^{o}C per decade) is almost twice the rate of change of the average between 1906 and 2005 (IPCC 2007) and this decade is seeing global rises at the same rate as the two previous decades (Hansen *et al.* 2010).

Potentially the most effective piece of evidence that recent climate variability is in part due to human activity is the observed rise in global CO_2 levels in the atmosphere. Figure 2-3 shows observations from Mauna Loa, Hawaii (Keeling *et al.* 2009). The intra-annual variability is largely due to the annual cycle of vegetation in the northern hemisphere, growing in summer months and dying in winter months. The rate of increase in atmospheric CO_2 has steadily accelerated since the beginning of the industrial revolution (1700s) due to human activities (burning of fossil fuels and deforestation) and levels are now approximately 35% higher (EPA 2012). Other less important anthropogenic greenhouse gases: methane and nitrous oxide have also increased rapidly largely due to agriculture (IPCC 2007).

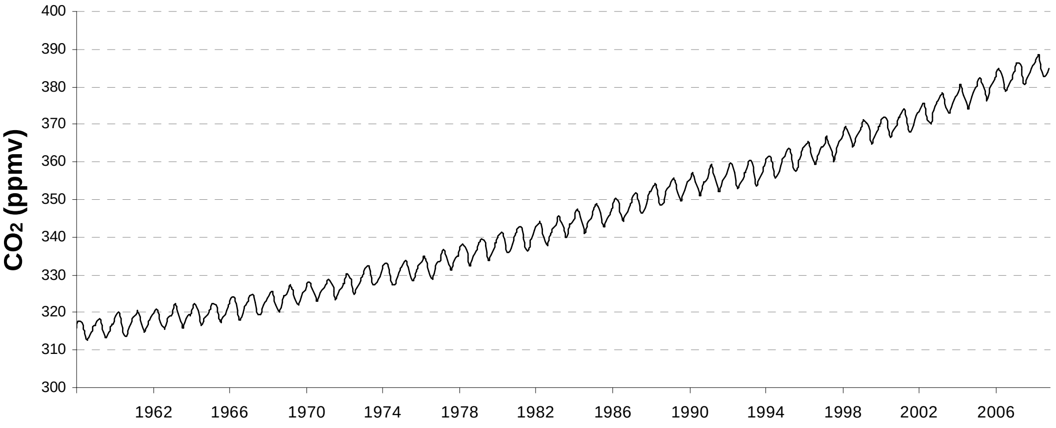


Figure 2-3: Historical CO_2 emissions observed at Mauna Loa, Hawaii

A more profound effect on human welfare than increasing global temperatures is the hydrological changes that will affect soil moisture and availability of water, all of which could have considerable negative impact on agriculture, especially in more sensitive regions. Medium and high latitudes are expected to have drier summers and wetter summers. Many other areas are predicted to have drier soil content over all seasons due to a decrease in precipitation and increase in evaporation (IPCC 2007, Wang 2005).

Both IPCC (2007) and UKCP09 (2009) include extensive data and discussion on the observed changes in the climate. The IPCC focuses on global change whereas the UKCP09 report focuses on the UK climate and recent observed trends. In the UK, as well as increases in temperature, other observed recent trends include more frequent wind storms, decreased summer rainfall, increased winter rainfall, and sea temperature and sea level rise (Jenkins *et al.* 2009).

2.2 Renewable Energy Resource, Technology and Vulnerability

Renewable energy technologies harness natural sources of energy and are therefore potentially susceptible to variations in the climate. Relatively small changes in the characteristics of a resource at a specific location can make the difference between a plant being economical or not. The following subsections briefly introduce different renewable energy technologies.

2.2.1 Solar Energy

Solar energy is the most abundant renewable energy source available on Earth. It presently counts for a very small proportion of generated energy, but growing concerns over climate change have helped stimulate a marked growth in implementation over recent years. This is expected to dramatically increase as solar technologies mature and costs significantly reduce.

Solar Photovoltaic (PV) has several key advantages when compared to other renewable energy technologies. Its modularity makes it extremely flexible – schemes can be upsized or downsized as required. PV systems that do not track the Sun have no moving parts and are therefore extremely reliable with very little operations and maintenance (O&M) overheads. It can be easily included in building products such as roof tiles and cladding. Financial risk is minimal due to the flexibility and reliability of PV (Awerbuch 2000).

The Solar PV contribution towards electricity generation in the UK is presently very small but installed capacity has increased considerably over recent years - from an estimated 10.5 MW in 2005 to 26.5 MW in 2009 (DUKES 2010). As of May 2010, installed capacity was estimated to count for approximately 0.3% of electricity generated from renewables in the UK with an installed capacity around 32 MW (PricewaterhouseCoopers 2010).

The recently introduced (2010) UK feed-in tariff (FIT) scheme, the aim of which is to promote small scale (<5 MW) renewable and low carbon electricity generation, has delivered very effective increases in the take-up of solar PV in the UK. From the introduction of the FIT scheme on 1st April 2010 through to 31st December 2010 saw a total of 19,723 installations under its scheme. 18,404 were PV installations (93.3% of all FIT installations), and as individual PV installation sizes are relatively small in size (<4 kW) compared to other technologies in the FIT scheme, the solar PV installed capacity counts for 66.8% (48.3 MW) of the total FIT installed capacity (66.8 MW) to date (OFGEM 2010). The effect of the introduction of the UK FIT scheme on solar PV can be clearly seen in Figure 2-4.

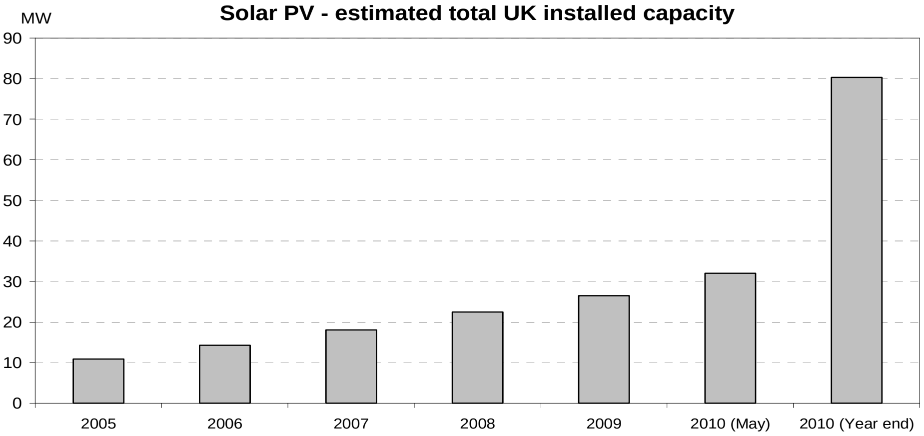


Figure 2-4: Solar PV Estimated UK Installed Capacity (PriceWaterHouseCoopers 2010, OFGEM 2010, DUKES 2010)

The IEA Solar PV roadmap estimates that 11% of global electricity demand will be provided by solar PV by 2050 (IEA 2010). The European Photovoltaic Industry Association (EPIA) have launched a project and set an industry roadmap to realise a 'vision' of solar PV in Europe with aggressive targets of providing 12% of electricity demand in 2020 (EPIA 2010a, European Commission 2010), 20% in 2020 and 30% in 2050 (EPIA 2010b). The UK FIT scheme is the legislative support that will help realise the UK's contribution towards Europe's PV target for 2020 and beyond. However, there have been recent developments that are currently a source of uncertainty for the FIT. A proposal by DECC to make large reductions to the solar FIT was branded as unlawful and rejected on the 21st December 2011 by a high court ruling on the grounds that the reduction would be inconsistent with the purpose of a FIT scheme (Shankleman 2012). DECC have lodged grounds of appeal with the appeal court and are currently awaiting a hearing date (DECC 2012). DECC is seeking to reduce the FIT because of a combination of accelerated PV deployment, falling installation costs, and increased electricity prices, which have resulted in higher than expected expenditure (DECC 2011).

2.2.2 Onshore and Offshore Wind Energy

The UK has excellent on- and offshore wind resources. Over recent decades onshore wind has grown considerably and is arguably the most mature of all renewable technologies excluding hydropower. UK installed capacity now exceeds 3.5 GW with up to 737 MW installed in 2008 alone (DUKES 2010). Offshore wind is still an emerging technology and not yet as mature a resource as onshore but it has huge potential. The UK presently has the world's largest offshore wind industry. As well as having good wind speed resource UK waters also benefit from being relatively shallow in many areas and ideal for offshore wind installations. There are 14 operational offshore wind farms with more than 1.5 GW of installed capacity (circa 2011). There is a further 2 GW in construction and 1.6 GW of approved installed capacity. (Renewable UK 2011a, 2011b). The most recent Round 3 leasing of sea bed for offshore wind by the Crown Estate brings the potential leasing installed capacity to over 40 GW (The Crown Estate 2011).

2.2.3 Wave and Tidal Stream Energy

Like offshore wind, the potential wave and tidal stream resource in UK coastal waters is large, especially wave energy. Both technologies are in the early stages of commercialisation and expected to mature over the next few years and to make a significant contribution towards the electricity technology mix over the next few decades. It has been estimated that by 2050 wave and tidal energy could contribute as much as 20% (~100 TWh) of the UK electricity demand (Carbon Trust 2006). The Crown Estate have recently granted six leases for wave and four for tidal stream in the Pentland Firth and Orkney vicinity. These developments alone are expected to reach an installed capacity total of 1.2 GW if they are fully developed (Crown Estate 2011, DUKES 2010).

2.2.4 Hydro Energy

Electricity generation from hydro is presently the most common and oldest source of electricity from renewable resources. Discounting pumped storage, it presently generates approximately 1% of the UK’s electricity (DUKES 2010). There are three main types of hydro electricity generation: The most common hydro system uses a dam to create a reservoir of water. The stored water can be released through turbines. In run of river hydropower partial flow from a river is re-routed through turbines close to the river. This method is more environmentally friendly, keeping the river more intact and unspoiled by a smaller weir but has less control due to no storage facility in the system. Finally, pumped storage has upper and lower reservoirs connected by pipes and pump-turbines. In periods of low electricity demand the turbines pump water to the higher reservoir; when demand is high, water is released from the upper reservoir back through the turbines to generate electricity.

2.3 Climate Change Impact on Electricity Generation Technologies

Electricity generation technologies can be affected by climate variability in several different ways: Solar energy can be affected by changing cloud cover characteristics (Crook *et al.* 2011, Pan *et al.* 2004). On and offshore wind can be affected by changing wind characteristics (Pereira *et al.* 2009, Prior *et al.* 2005a, 2005b, 2009). Wave energy can be affected by the effect of wind speed on wave resource characteristics (Cradden 2009, Harrison *et al.* 2005, Lowe *et al.* 2009, Reeve *et al.* 2011, Wang *et al.* 2004, Woolf *et al.* 2002). Hydropower can be affected by changes in precipitation and evapotranspiration (Harrison *et al.* 2003; Vicuna *et al.* 2007). Tidal stream characteristics are not expected to be affected significantly by climate change as they are caused by gravitational influences between the moon, the sun, and the earth. However, increasing temperatures will cause seas to rise, and this may alter site specific tidal characteristics of potential tidal stream locations. This could be tested by modelling several potential tidal stream farm locations and testing the efficiency for varying water depths. Many potential tidal stream locations are in extremely harsh locations and have limited windows where conditions are suitable for TEC deployment and maintenance – increased storm activity due to climate change will both increase survivability issues and limit weather windows even further and could be the deciding factor whether a potential site is economical or not (Harrison *et al.* 2005). Thermal plant can be affected by reduced temperature gradients in cooling systems and by low levels in water sources for cooling systems such as rivers or reservoirs (Florke *et al.* 2010, Greis *et al.* 2009). Biofuels can be affected by the impact on crop yields; the use of biofuels is also vulnerable to the balance of global food supply and demand, which in turn is at risk from climate change impact (Cassman *et al*. 2007, Lobell *et al.* 2008). This study assumes that tidal stream, thermal plant and biofuels are unaffected by climate change.

2.4 Energy Economics and Risk

2.4.1 Levelised Cost of Electricity Generation

The cost of electricity generation is typically expressed as a unit of levelised cost (also known as levelised unit costs or unit costs). In the case of electricity generation all discounted costs throughout a plant’s lifetime are apportioned by the total discounted electrical output of the plant. The resulting figure is then expressed as a cost per unit of electricity output (e.g. £/MWh or p/kWh).

Levelised cost estimations are frequently used to make comparisons between different generation technologies or to compare a specific technology at different locales where associated costs and resources have the potential to be quite different. They are also often used as a source of data for policy makers and can help identify future electricity generation mixes of technology and indicate levels of support that may be needed by individual technologies, especially emerging technologies that are generally more expensive while they develop into a mature technology (IEA 2010).

Levelised costs are collated and published in many government and energy related reports. (e.g. IEA 2010b, Mott McDonald 2010) The range of levelised costs estimations over different reports can vary quite significantly and can lead to some controversy. Heptonstall (2007) carried out a useful review of levelised cost literature, the ranges of costs for each technology and discussed the possible reasons for the variations. There are a large number of factors that can be very difficult or impossible to accurately estimate e.g. financial risk; benefits through increased diversity; portfolio value; price variations; renewable resource variations, external costs and benefits. Several of these factors are discussed in more detail by Gross *et al.* (2007) and Heptonstall (2007).

Levelised costs are used extensively in chapters 6.4 and 0. The method used in this study is the annual 'discounting' method which is the method generally used in levelised costs of electricity studies (Carbon Trust 2010, IEA 2010, Mott MacDonald 2010, UKERC 2010)

$$LC_D = \frac{PV(Costs)}{PV(Output)} = \frac{\sum_{t=0}^{n} C_t \big/ (1+r)^n}{\sum_{t=0}^{n} O_t \big/ (1+r)^n} \tag{2-1}$$

Where LC_D is the discounted levelised cost of electricity (£/MWh), *PV(Costs)* is Present Value of total costs, *PV(Output)* is Present Value (PV) of electricity generation (MWh), C_t is the total costs in the operating year, O_t is the total generation in the operating year (MWh), n is the operating year of the of the plant, and r is the annual discount rate.

The discounted levelised cost of a technology is its discounted average cost to generate one unit of electricity to the electricity network over the operational life time of the installation. The discounted levelised cost generally does not include all system costs. The purpose of the discount rate is used to value a future cash flow at its present day value. The value of discount rate chosen is to suit the financial risk of the future cash flow.

2.4.2 Financial Risk

Economic appraisal of renewable electricity generation technologies are often undervalued when compared to more traditional fossil-fuel based electricity generation technologies and assumed to have the same risk profile. Engineering projects are often valued by a least-cost method, such as a levelised cost, where lenders and investors can be largely unaware of additional costs relating to the financial risk inherent in the project. Levelised cost comparisons often use the same discount rate across all technologies and in doing so implicitly assume they all have the same risk profile. Care should always be taken when comparing levelised costs. Different assessment methods and assumptions can significantly affect the levelised cost values. If the assumptions and methods vary between technologies and reports then levelised costs are not easily comparable. Also, studies do not always publish full details of the methods and assumptions used. This can make it very difficult to attain confidence in the values or to understand any inconsistencies between different reports.

The Capital Asset Pricing Model (CAPM) first introduced by Sharp (1964) is extensively used in financial economics as a tool to capture risk and expected return in an investment by deriving a discount rate applicable to the associated risk. CAPM states that the expected return is a function of risk: the higher the risk, the higher the return required to compensate for that risk. In the context of financial markets, western government debts are regarded as risk free. The CAPM has been used by Harrison *et al.* (2003) to look at climate impact on hydro. It has also shown fossil fuelled electricity generation to be significantly more risky than traditional estimates imply (Awerbuch *et al.* 2005).

The Capital Asset Pricing Model can be calculated by:

$$R_i = R_f + \beta\left(R_m - R_f\right) \qquad \textbf{(2-2)}$$

where R_i is the expected return of the asset, R_f is the risk free rate of return, β is the beta correlation which relates the expected return of an asset and the expected return of the wider market and R_m is the expected return of the market.

Awerbuch (2000) suggested that photovoltaics (PV) and other renewable energy technologies are undervalued. He explains that the financial models used to evaluate new renewable technologies were developed for a past technological era and they do not capture benefits over traditional riskier fossil fuel technologies or capture the benefit of increased diversification and resulting benefits to security of supply. New renewable technologies consequently suffer from evaluation with discount rates more suitable for a riskier investment.

Newer renewable technologies may have higher initial capital costs than other traditional technologies, but can benefit from qualities such as increased flexibility, modularity, lower risk, no fuel price and lower operating costs. Awerbuch (2000) argues that policy makers should introduce new models that can fully capitalise on the unique qualities of PV and other technologies with similar attributes. He illustrates a method of using market-based discounting rather than the more traditional approach of weighted average cost of capital (WACC) to adjust the discount rate relative to the lower risk and to realise the real economic value of solar PV and other emerging technologies.

Awerbuch (2000, 2003, 2003b) also argues that as well as renewables costs being significantly overestimated that also conventional technology costs are underestimated when adjusted to include fuel price variability. Figure 2-5 shows Awerbuch’s risk-adjusted technology costs of electricity. Understandably, one of his main conclusions are that that renewable technologies are ‘considerably more cost-competitive than previously believed’ Awerbuch (2003b). In one example he demonstrated that the risk associated with gas price variability reverses the merit order between CCGT and wind (Awerbuch *et al.* 2005). Rapid fluctuations in gas prices in the UK over the last 3 or 4 years are a good example of such volatility.

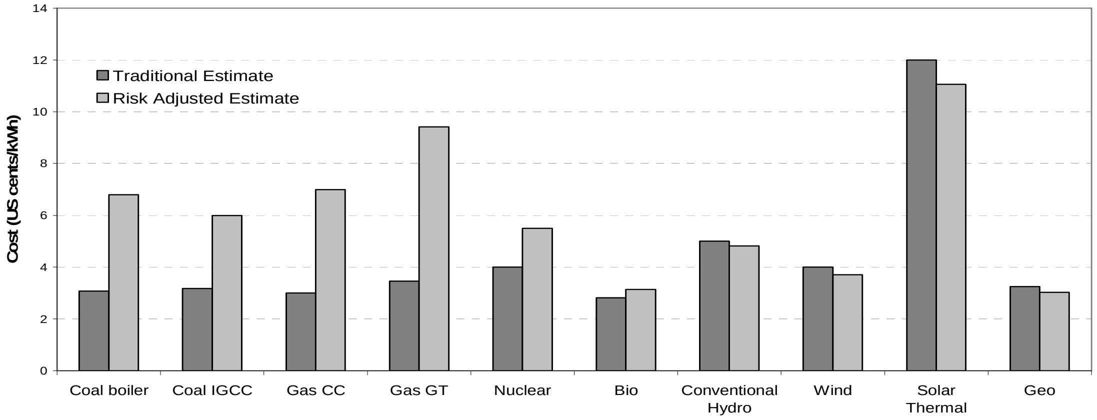


Figure 2-5: Risk adjusted cost of electricity estimates (Europe/IEA countries) based on historic fuel price risk. (Awerbuch 2003b).

As mentioned previously one of the failings of a levelised cost comparison is its assumption that all technologies have the same risk profile. Comparisons in this study are made using a single discount rate. MVPT analysis determines the combined risks of a portfolio. Levelised cost assumptions that need to be carefully chosen as they can significantly affect the levelised cost values include the discount rate, capital cost, fuel and O&M costs, average load factor (capacity factor) and operational lifetime.

A further failing of valuation by a least-cost method is that it does not capture the benefits of diversification. An installation when valued as part of a portfolio of installations may be significantly more valuable when measured by its contribution to the cost and risk of a portfolio of technologies. A portfolio of different electricity generation technologies can be combined in such a way as to reduce cost or risk, or a combination of both. This is made possible by benefiting from the diversification between the technologies.

2.5 Mean Variance Portfolio Theory

Mean Variance Portfolio Theory (MVPT) was introduced by economist Harry Markowitz (1952) as a tool to help investors optimise their financial portfolio assets. Investors understandably like assets with high returns, but high risk is inherent with high return investment. Markowitz devised a method to reduce the risk in an investment by grouping a risky asset with other diversified assets in an investment portfolio. In doing this the overall portfolio risk can be reduced in comparison to any of the individual assets as it changes the overall risk from the individual risk to the contribution of its co-variance with the other asset risks. This can result in a significant reduction of overall risk with little change to the expected return of the investment.

The expected portfolio return $E(R_p)$ of two assets is equal to the sum of the expected return of each asset weighted by its share of the portfolio:

$$E(R_p) = X_1 E(R_1) + X_2 E(R_2) \qquad \textbf{(2-3)}$$

where X_1 and X_2 are the proportions of each investment, and $E(R_1)$ and $E(R_2)$ are the expected returns of each investment. Return in this sense means how well the investment generates cash flow relative to the invested capital. The portfolio risk is a measure of standard deviation of past returns and can be calculated by:

$$\sigma_p = \sqrt{X_1{}^2\sigma_1{}^2 + X_2{}^2\sigma_2{}^2 + 2X_1X_2\sigma_{12}{}^2\sigma_1\sigma_2} \qquad \textbf{(2-4)}$$

where σ_p is the expected portfolio risk, σ_1 and σ_2 are the risks of each investment, and σ_{12} is the correlation coefficient of the historic return between the two assets.

Figure 2-6 demonstrates how MVPT can be used to optimise a portfolio of two investments with different expected returns and risk. The two assets have a historic correlation coefficient of -0.3 (i.e. assets have a negative correlation). The curved line shows the expected portfolio return and risk for different weightings of the assets. At extreme ends are portfolios containing only Investment 1 or Investment 2. The red part of the curved line shows the efficient frontier on which any point is an efficient portfolio mix where the portfolio is optimised for either a maximum return for a given expected risk, or a minimum risk for a given expected return.

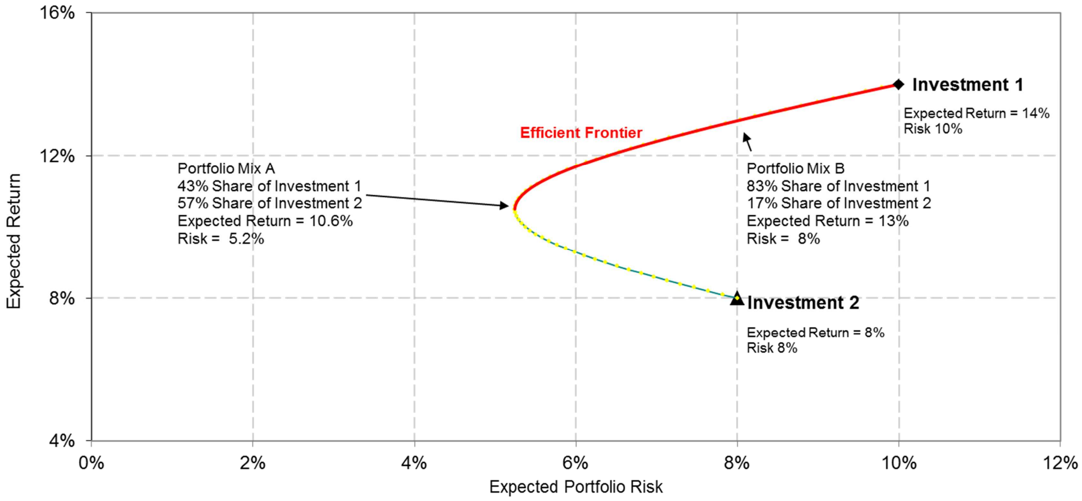


Figure 2-6: Two investment example of MVPT

As can be seen in Figure 2-6, Investment 1 has a much better return than Investment 2 but it also has much higher risk. By adding in a proportion of Investment 2 to Investment 1, the overall investment risk can be significantly reduced for a relatively small reduction in overall return. The red line is known as the *Efficient Frontier* and any one point on the line shows an optimal portfolio mix. An optimal mix is where the highest possible return for the lowest possible risk is shown. There is no wrong or right point on the efficient frontier, all are optimal and the chosen mix would be based to suit the investor's risk-return preferences. Portfolio mixes A and B are two optimal mixes on the efficient frontier, Portfolio A shows a low risk but low return, portfolio B is a medium risk with medium return; the choice is with the investor. MVPT also applies to models of more than two investments.

2.5.1 Diversity and MVPT

With CO_2 emission reduction targets, scarce fuel resources and volatile fuel prices, it is understandable that there is much interest in the benefits of a diverse electricity generation mix with a high proportion of renewables. There is a lot of academic, governmental and market interest and research activities investigating how to optimise energy portfolios so as to capitalise on the available benefits gained from diversification. These include: security of supply, reduced financial risk to volatile fuel prices, and reduced overall costs to society. There are synergies between security of supply, renewables and the reduction of CO_2 emissions, which further enhance the importance of a diversified mix of generation technologies.

Skea (2010) summarises recent academic studies of diversity and electricity generation and discusses two distinct 'strands' of research literature. The first strand, most notably researched by Awerbuch *et al* (2003, 2006, 2007) uses MVPT to investigate optimal portfolio mixes using basic statistical analysis based on historical pricing information with the assumption that future volatility will be captured from events in the past. The second strand looks specifically at security of supply and quantifying diversity, not just from 'risk' - captured in historic events but also from 'uncertainty' – potential future events that are foreseeable but have not happened in the past; and from 'ignorance' – potential future events that have not even been considered. The method uses indices such as the Shannon-Wiener index (Grubb *et al.* 2005, Stirling 1994) to try and quantify 'disparity' – how different the different technologies actually are. Stirling (1994) argues that MVPT is not a suitable application to use to investigate electricity generation portfolios as historic fuel price fluctuations have no pattern; Awerbuch (2003) argues that MVPT is suitable, that it captures 'total risk (the sum of random and systematic fluctuations) measured in the standard deviation of periodic historic returns'. Awerbuch's point is that although certain historic events may not happen again, the actual effect of these unique events will be repeated.

2.5.2 Electricity Generation and MVPT

The primary objectives of identifying a future optimal electricity generation mix are to:

- Reduce the extent of climate change by cutting CO_2 emissions.
- Ensure the security of energy supply by having a diverse energy mix; Provide affordable energy to society.

It is widely accepted that diversification of electricity generation technologies can reduce some of the risks to energy supply and increase security of supply. However, as previously mentioned, a traditional ‘levelised cost’ method of technology comparison does not capture the risk characteristics associated with different technologies and undermines the financial benefits associated with renewable technologies due to reduced financial risk within a mix including traditional generation technologies risks of fuel and carbon price variability.

The application of MVPT in energy systems was first explored by Bar-Katz and Levy (1978) who applied MVPT to electricity generation raw fuels in the U.S. to generate efficient frontiers for different regions and compare them with the actual observed values. Awerbuch and Berger (2003) use the same approach to investigate optimal EU electricity generation mixes and the role that renewables can play in reducing overall costs and risks by capitalising on renewables having no fuel costs. Awerbuch has used MVPT for several other studies (e.g. Awerbuch 2003, 2005, 2006, 2007). There are a growing number of studies of energy using MVPT - often following on from Awerbuch’s early work (Delaquil *et al.* 2005, Doherty *et al.* 2006, Grubb *et al.* 2006, Jansen *et al.* 2004, Roques *et al.* 2006a, White 2007). Bazilian and Roques (2008) includes much of the significant research in this area.

Figure 2-7 gives a hypothetical example of MVPT and two electricity generation technologies (Solar PV and Gas Generation). Rather than MVPT being used for maximising return, here it has been modified to minimise the cost of electricity on a p/kWh basis. The technology generating cost is its levelised cost; the portfolio generating cost is the weighted levelised cost of all technologies in the portfolio mix. The technology risk is a measure of the historical standard deviation of the levelised cost components weighted by their energy contribution.

As can be seen the efficient frontier is now on the lower side of the curve. It is not on the upper side of the curve as for any point on the upper side a lower generating cost of electricity exists for the same level of risk. It is also feasible to use MVPT as a generator return tool – i.e. net present value, but this requires significant extra complexity associated with the need to model market prices.

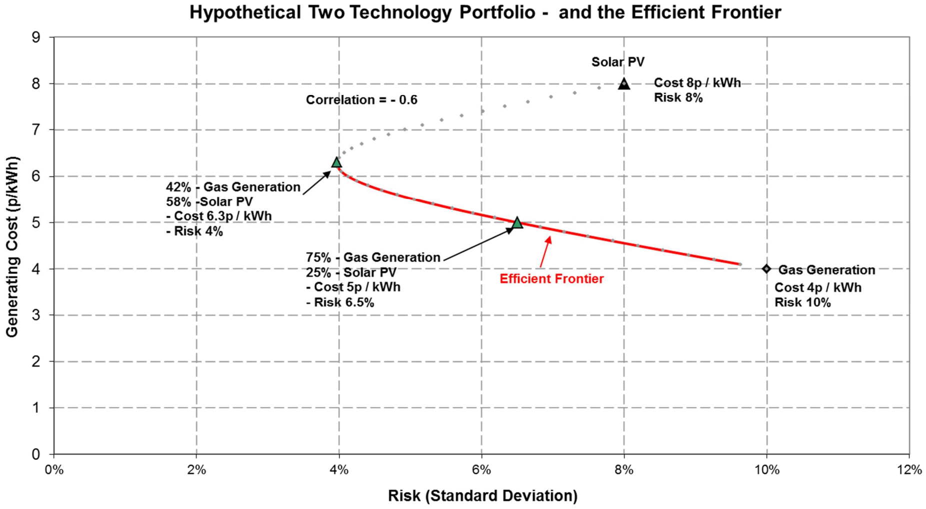


Figure 2-7: Two hypothetical generation technology example with MVPT optimising for minimal generating cost.

Previous Electricity Generation MVPT Studies

Awerbuch *et al.* (2003) used MVPT to evaluate electricity generation technologies and the projected technology mix in the EU for 2010. By applying MVPT a more efficient mix could be identified where expected cost is minimised for any given level of risk or the level of risk minimised for the expected cost of the portfolio of technologies. Even though renewable technologies were nominally more expensive, the study showed that the different renewable and fossil-based generating technologies could be combined to form a less costly portfolio than a portfolio with just fossil-based technologies. Renewables are not without risk but have both lower and different risk characteristics than fossil fuelled technologies. MVPT optimises portfolio mixes by capitalising on the diversity of the risk characteristics of the different technologies. Several similar MVPT studies to Awerbuch *et al.* (2003) have since been carried out:

Awerbuch (2005a) investigated optimal energy mixes for the UK. The outcome found that DTI 2010 and 2020 target mixes were not optimal. Optimal mixes with less risk and no extra costs were found, these having increased shares of offshore and onshore wind. Awerbuch (2005c) looks specifically at Scotland and has a similar outcome to Awerbuch (2005a) with optimal mixes having increased share of wind generation and other renewable technologies.

Awerbuch *et al.* (2005b) investigated geothermal energy, portfolio theory and optimal mixes in the US western region for 2013. The present energy mix and the Energy Information Administration (EIA) target mixes for 2013 were found to be sub-optimal. Optimal mixes had increased shares of geothermal energy.

DeLaquil *et al.* (2005) examined different possible optimal mixes for Renewable Portfolio Standard (RPS) legislation being considered by the Commonwealth of Virginia. Optimal mixes for a 2015 scenario were found to significantly reduce financial risk when compared to EIA projections. A 15% renewable energy RPS scenario was found to reduce risk by 25% to 30% with negligible increase in cost. A further benefit detailed in the report was that the reduced gas demand would result in reduced gas prices and an annual net saving to the Virginian consumers in excess of $30 million.

White (2007) investigated future portfolios for California specifically to identify efficient mixes capable of increasing the mix of renewables by 33% by 2020. The outcome of the report suggests that optimal generation mixes to reach the target could also reduce costs and risks of California's energy mix when compared to a non-target business as usual (BAU) scenario.

Doherty *et al.* (2006) assessed generation portfolios in the island of Ireland and concluded that wind generation has a large part to play in future optimal generation portfolios. McLoughlin *et al.* (2006) investigated Republic of Ireland projected generation mixes for 2020 with the analysis showing the mixes to be non-efficient. With increased energy generation diversity, most notably wind generation and biomass, the study concluded that reductions of up to 43% risk and 12% cost could be obtained.

Jansen *et al.* (2006) investigated projected generation mixes in the Netherlands for the year 2030. Two scenarios constructed by the Netherlands Bureau for Economic Policy Analysis (CPB) were both found to be quite inefficient. The study found that up to 20% risk reduction, with no extra cost, could be gained by adding more offshore wind to the energy portfolio.

Carbon Pricing, Diversity and MVPT

Carbon pricing methods are being introduced to control and reduce CO_2 emissions. It is clear that as the carbon price increases, future efficient portfolios will become costlier and riskier due to the added cost and risk of the carbon price. Efficient portfolios will most probably need to consist of smaller proportions of carbon intensive fossil fuel technologies. This was demonstrated in an analysis of the EU electricity generating mix performed by Awerbuch *et al.* (2007). Carbon pricing was initially set at zero then set at €35/t CO_2. A business as usual (BAU) EU projection mix for 2020 was found to increase by 23% in cost and 40% in risk. An optimal mix identified as having the same risk as the BAU case but with lower cost, saw a reduction in emissions from 1450 to 725 million tonnes of CO_2 per year when the carbon pricing was stepped up from zero to €35/t CO_2.

Grubb *et al.* (2006) explored characteristics of projected future electricity mixes up to 2050 and compared it to alternative low carbon scenarios. The outcome found that low-carbon objectives were ‘uniformly associated with greater long-term diversity in UK electricity generation’, i.e., the low-carbon scenarios were found to be more diverse and therefore, more secure than the projected scenarios. The study found this was largely due to the share of gas in the UK electricity generation mix.

2.5.3 Policy towards a low carbon future

This study is closely aligned with a common European energy policy which was agreed and created in 2007. The policy describes a pathway towards 2020 which is based on three pillars: Sustainability, Security of Supply and Competitiveness (Commission of The European Communities 2007). The pillar of ‘Sustainability’ recognises that the current level of greenhouse gas (GHG) emissions from energy related activities is by far the largest contributor towards climate change and is not sustainable. The new policy aims to limit the global temperature increase to within 2ºC of pre-industrial times for 2020 and beyond. The pillar of ‘Security of Supply’ recognises the growing dependencies on imports of oil and gas and the associated economic and political risks as well as the increased risk of actual supply failure. The new policy aims to enable internal predictable and effective markets with competitive prices. The pillar of ‘Competitiveness’ recognises the growing volatility of gas and oil and the potential total cost of imports. The new policy aims to improve competitiveness through new legislative frameworks that can promote competitive prices and energy savings which would entail increasing investment in renewables and energy savings.

Also of close alignment is with the UKERC 2050 Project (UKERC 2009) exploring low-carbon energy pathways towards 2050 that achieve an 80 per cent reduction in carbon emission (from 1990 levels) while ensuring a secure and resilient energy system. The UKERC 2050 project uses the UK MARKAL elastic demand (MED) model to explore different energy sectors including electricity generation. There are several scenario outcomes, each with its own specific CO_2 reduction target and energy mix.

Low carbon renewable electricity generation can dramatically help the UK meet the policy requirements by reducing CO_2 emissions from electricity generation, as well as gas oil and coal imports, while also increasing the diversity and security of supply. Mean Variance

Portfolio Theory (MVPT) can offer an analysis method that can identify diverse low carbon electricity generation mixes with optimal cost-risk characteristics. However, electricity generation portfolios and particularly those with high proportions of renewable electricity generation are expected to be affected by climate variability impacting the resource.

2.5.4 Policy Implications and MVPT

Planners and policy makers wanting to aim towards a chosen future electricity generation mix may need to introduce new mechanisms to add incentives to steer investors towards a target mix. There are already several mechanisms already in place to reduce carbon emissions and support emerging and mature renewables, which include: green certificates feed-in tariffs, and the EU emissions trading scheme. Skea (2010) highlights that there may not be any need to introduce any further policy incentives to optimise diversity as it may be ‘overkill’. Skea also states that ‘there is no “right” level of diversity’ and is something to be ‘determined politically’.

Portfolios that feature a high proportion of less risky renewable technologies could be used to steer the development of future UK electricity utilities towards a secure and more resilient energy mix that is less susceptible to fuel price variability. It also acts as an aid towards meeting new renewables and carbon emission targets (Awerbuch 2006, Jansen 2004). Energy planners would need to adopt MVPT techniques and introduce new policies to steer investors towards a target optimal mix. The optimal economic investment from a utility point of view is likely to be quite different from the optimal societal investment and new policies would need to be effective. Solutions may include some diversity tax incentives for utility developers (Roques *et al.* 2006). There may be a similar strategy to that of the present Renewables Obligation Certificates (ROC) system which raises returns for renewable energy investment albeit with an additional ROC price risk.

2.5.5 Assumptions and Limitations of MVPT

MVPT uses historic standard deviation of the associated costs as a guide to future risk. This includes previous ‘random’ events that have happened within the historic period, but it does not capture any potential future extreme events.

Electricity generation technologies are inherently lumpy, their capacities are not infinitely divisible in the way that stocks and shares are; they cannot be easily adjusted in size to suit an optimal portfolio. This creates difficulty in applying portfolio theory in real electricity generation situations.

Some transition costs from a present portfolio mix to a future portfolio mix may not be fully captured. For example, if existing plant needed to be decommissioned earlier than planned it may result in the plant being less economical. These costs include decommissioning and salvage.

MVPT does not capture real time requirements of electricity generation, nor does it capture any associated resource and technology limitations. These are instead controlled by external constraints applied on the MVPT analysis (see section 8.2.2).

2.6 Climate Change and MVPT

MVPT has been used in recent studies as a method to investigate optimal electricity generation mixes, the financial benefits of renewable energy and their contribution towards security of supply. These studies are extremely useful for assisting electricity generation investors, governments and policy makers to steer future development towards a socially optimal mix benefiting from a high degree of diversity and minimal level of financial risk. Previous electricity generation studies using MVPT have assumed constant energy production from renewable and non-renewable sources. However, the studies conducted to date so far have had potential shortcomings in that they assume constant energy production from renewable sources. The cost-risk economic models of renewable technologies are inherently sensitive to resource variability - projected optimal generation portfolios based on resource characteristics of the present climate may change significantly when the additional resource variability due to climate change is considered.

With levelised costs of renewables very strongly influenced by assumptions over resource levels, it is reasonable to expect that optimal generation portfolios would change where resource levels change as climate changes. As such, this work will concentrate on understanding current and future resource for key renewable generation technologies with a view to understanding the implications for future optimal portfolios.

To this effect, the following chapters consider changes in resource levels for solar PV, wind, wave and hydropower, before bringing all the economic impacts together in a MVPT analysis in chapter 8.

2.7 Chapter Summary

This chapter has provided the reader with a background to the different fields required to answer the hypothesis. Climate change and climate projections with particular emphasis on the UKCP09 probabilistic projections are introduced. Renewable technologies and their resource are briefly discussed. Energy economics, financial risk and Mean Variance Portfolio Theory (MVPT) are discussed. It has not been intended as an exhaustive literature survey of all material, it is a targeted effort to equip the reader with sufficient background knowledge in the main topics covered in this thesis.

3 Solar Energy

3.1 Introduction

The main objective of this chapter is to assess the baseline solar resource of the UK and investigate the impact climate change could have on the resource and output from solar photovoltaic (PV) cells. It uses probabilistic regional climate change scenarios released as part of the United Kingdom Climate Projections study (UKCP09).

The yellow blocks in the thesis flowchart (Figure 3-1) signify the areas of the thesis connected with this chapter.

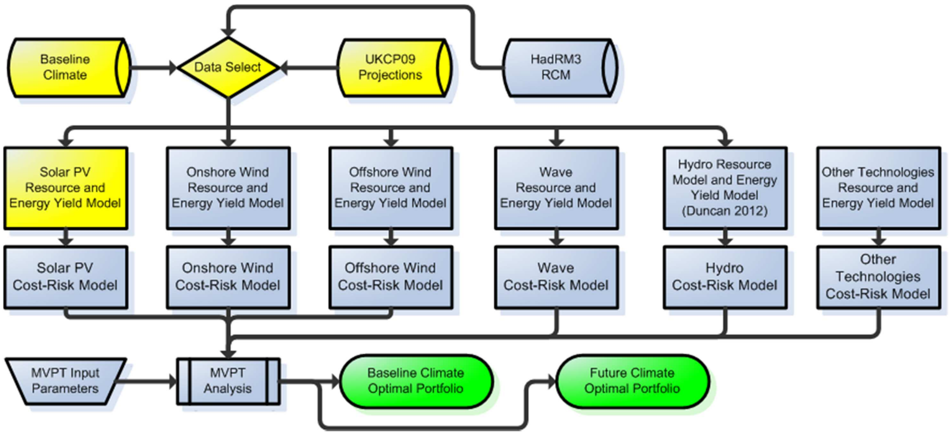


Figure 3-1: Thesis flowchart and solar energy resource blocks

3.1.1 Chapter overview

Solar radiation data is measured at several weather stations but many lack historical data. Sunshine data is far more plentiful with excellent geographical coverage and historical data far in excess of 30 years. The Met Office have used much of the UK's observed sunshine duration data to develop annual monthly average 5km x 5km gridded data sets of daily sunshine duration over the UK. The gridded data sets cover in excess of 30 years and were used as the main source of observed sunshine duration. The sunshine data was converted to solar radiation using a method described by Suehrcke (2000), then averaged over the 30 year baseline period. Verification was achieved by comparing with actual observed solar radiation data from weather stations located at several locations throughout the UK. The baseline solar resource model was converted to solar resource on a south facing incline, which increases available resource by facing more directly towards the Sun. The incline is a typical characteristic of solar panel installations. The UK was split into six different solar regions, resource characteristics were explored and proportions of solar deployment were estimated for each region. The proportioned regional characteristics were used to generate solar PV output resource values for the UK. Output from the UKCP09 probabilistic climate change projections were used to explore how solar PV resource may change throughout the UK. The projected change for each of the solar regions and the resulting change in the UK solar PV output values were investigated.

3.2 Baseline Resource

The aim of the first part of the section was to create an accurate geographical map of solar energy resource over the UK to represent the present (baseline) climate. There are two main parameters measured at weather stations that can be used to estimate solar radiation resource. Solar radiation is directly measured using a Pyranometer. An alternative method of estimating solar radiation is by converting sunshine duration as measured using a Campbell Stokes Recorder.

Pyranometers directly measure solar radiation using a thermal sensor. There are various types of Pyranometer, the most common type measures both ‘direct’ (directly from the Sun) and ‘diffuse’ (indirectly from the clouds and sky) horizontal solar radiation. Less common devices, which require mechanical adjustment of apparatus to either track or block the Sun, measure just the ‘direct’ or ‘diffuse’ part. Solar radiation is recorded at several observation stations across the UK but in much fewer numbers and with shorter historic time series than sunshine duration observations. Pyranometer measurements may have systematic errors of up to 10% due to varying outdoor field conditions (IEA 1995).

The Campbell-Stokes Recorder produces daily sunshine duration data by converging the rays of the sun through a glass sphere onto a strip of chemically treated paper. The equipment was first introduced in the late seventeenth century and is still the official method of recording sunshine duration hours. Present designs have changed very little; it is relatively simple in design and easily maintained. The UK Met Office holds daily sunshine duration data for in excess of 200 Campbell-Stokes Recorders situated in various observation locations throughout the UK.

3.2.1 Sunshine Duration to Solar Radiation Conversion Method

Sunshine duration data was used to develop the solar energy resource map. The UKCP09 observed gridded data sets include monthly averaged sunshine duration hours at a resolution of 5km. The gridded data sets are based on weather station sunshine hour observations. The raw data has been subjected to regression and interpolation to generate data at regularly spaced grid points from the irregularly spaced network of measurement stations. The dataset output also takes into account other attributes such as location, altitude, terrain, coastal influence, and land use (Perry *et al.* 2005a, 2005b).

The approach taken was to generate a geographical model of monthly / seasonal global radiation data of the UK by converting UKCP09 / Met Office 5km gridded sunshine duration hours (UK Meteorological Office 2009a) to global radiation. The method used was introduced by Suehrcke (2000). It is based on the widely used Angstrom-Prescott equation that describes a relationship between the relative sunshine duration and solar radiation on the surface of the earth. (See Martínez-Lozano *et al.* (1984) for a historical appraisal of the evolution of the Angstrom-Prescott equation). The advantage that the Suehrcke method has over the Angstrom-Prescott method is that it does not rely on two empirically derived constants that vary quite considerably depending on location. Instead, the Suehrcke method requires only an estimate of the monthly average daily clear sky clearness index. Suehrcke (2000) states the value as being ‘typically between 0.65 to 0.75’.

3.2.1.1 Suehrcke Conversion Method

Monthly average values of daily sunshine duration data was first converted to solar radiation using Suehrcke’s derived equation which relates the sunshine fraction to monthly average of daily horizontal extra-terrestrial solar radiation (Suehrcke 2000). The process of relating sunshine hours to solar radiation on a horizontal plane requires the calculation of several other parameters. These include: length of the day, sunrise or sunset hour angle, declination of the sun and extra-terrestrial solar radiation. They use several commonly used empirical equations 3-2 to 3-7 which are described in many standard solar resource textbooks (Garg *et al.* 2000; Sukhatme *et al.* 1996, Twidell *et al.* 2006) are used to estimate the mentioned parameters. All calculations assume that cloud cover has uniform characteristics throughout the day, and solar radiation is isotropic.

Suerchke's equation is

$$f_{clear} = \left(\frac{\overline{K}}{\overline{K}_{clear}} \right)^2 \tag{3-1}$$

where f_{clear} is the fraction of time which no significant clouds block the sun, $\overline{K}$ is the monthly average daily clearness index and $\overline{K}_{clear}$ is the monthly average clear sky clearness index.

The variable f_{clear} for a specific month and location is equivalent to the sunshine fraction *(S)*. The sunshine fraction can be calculated by dividing the average monthly sunshine duration data by the average monthly day length. Day length can be calculated by

$$N = \frac{2}{15} \cos^{-1}(-\tan\phi \tan\delta) \tag{3-2}$$

where N is day length in hours, ϕ is the latitude in degrees and δ is the declination of the sun in degrees. Declination of the Sun (δ) can be calculated by

$$\delta = 23.45 \sin\left[360 \frac{284+n}{365} \right] \tag{3-3}$$

where n is the day of year starting on 1st January.

The monthly average clear sky clearness index $\overline{K}_{clear}$ is the component in Suehrcke's equation that removes the requirement of the two empirical constants in the Angstrom-Prescott method. The monthly average clear sky clearness index.

$\overline{K}_{clear}$ can be calculated by

$$\overline{K}_{clear} = \frac{\overline{H}_{clear}}{\overline{H}_{o}} \tag{3-4}$$

where $\overline{H}_{clear}$ is the monthly average of daily horizontal surface clear sky radiation (J m^{-2}) and $\overline{H}_{o}$ is the monthly average of daily horizontal extra-terrestrial solar radiation (J m^{-2}).

The daily horizontal extra-terrestrial solar radiation variable H_o can be calculated by

$$H_o = \frac{3600 * 24}{\pi} I_0 * \frac{\pi h_{ss}}{180} \left(\sin\phi \sin\delta + \cos\phi \cos\delta \sin h_{ss} \right) \tag{3-5}$$

where I_{sc} is the solar constant and is equal to 1367 W/m^2, h_{ss} is the sunrise / sunset hour angle on a horizontal surface and I_o is the extra-terrestrial solar radiation at normal incidence. h_{ss} can be calculated by

$$h_{ss} = \cos^{-1}(-\tan\phi \tan\delta) \tag{3-6}$$

while I_o can be calculated by

$$I_o = I_{sc} \left(1 + 0.033 \cos \frac{360}{365} n \right) \tag{3-7}$$

Unfortunately $\overline{H}_{clear}$ is a parameter that is not readily available from observed data. Therefore, an alternative method of determining $\overline{K}_{clear}$ has been used: Monthly $\overline{K}_{clear}$ values were identified by calibrating the value of $\overline{K}_{clear}$ in the Suehrcke conversion equation against actual observed solar radiation data. This process essentially makes it empirical.

3.2.1.2 Resource Analysis

Eighteen UK meteorological stations were identified that record both sunshine duration and solar radiation, they had both Pyranometers and Campbell Stokes recorders, and also had sufficiently long historical data for both parameters. A daily time series of 5 years (1995 to 1999) of both sunshine duration and radiation was downloaded for all eighteen met stations (Met Office 2006) and used for the analysis of the $\overline{K}_{clear}$ values.

The average monthly converted sunshine duration values for all stations were adjusted to match the average observed monthly global solar radiation by optimising the value of $\overline{K}_{clear}$ for each month. The eighteen locations are shown in Figure 3-2. The UK values for $\overline{K}_{clear}$ are shown in Table 3-1. The monthly $\overline{K}_{clear}$ variability between the stations and the $\overline{K}_{clear}$ Root Mean Square Error (RMSE) are shown in Figure 3-3.

The RMSE can be calculated by

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(X_i - \overline{X}\right)^2}{n}} \tag{3-8}$$

where X_i is the met station $\overline{K}_{clear}$ value, $\overline{X}$ is the average of the met station $\overline{K}_{clear}$ values, and i is the met station number.

There appears to be no correlation between the $\overline{K}_{clear}$ and latitude or longitude of location. For instance, three stations that have marginally higher values (src113, src1198, src1395) are located in North Scotland, Wales, and South West England respectively.

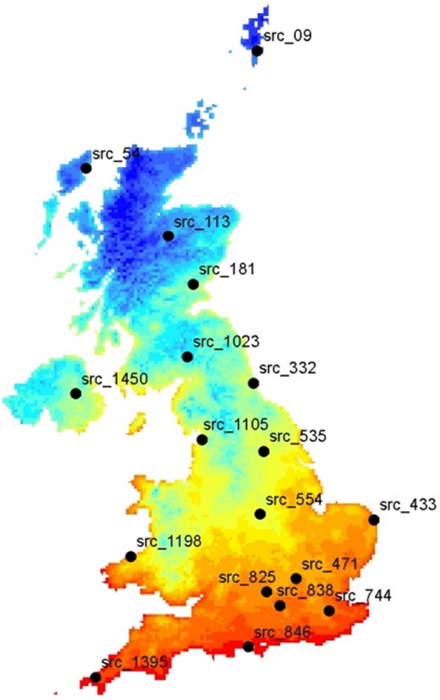


Figure 3-2: Locations of met stations measuring both sunshine duration and global radiation

Month	Average $\overline{K}_{clear}$	RMSE
January	0.579	0.0259
February	0.63	0.0275
March	0.668	0.0254
April	0.682	0.0243
May	0.701	0.0169
June	0.707	0.0305
July	0.71	0.0191
August	0.679	0.0165
September	0.667	0.0160
October	0.641	0.0249
November	0.628	0.0332
December	0.616	0.0738

Table 3-1: Average $\overline{K}_{clear}$ values for the UK

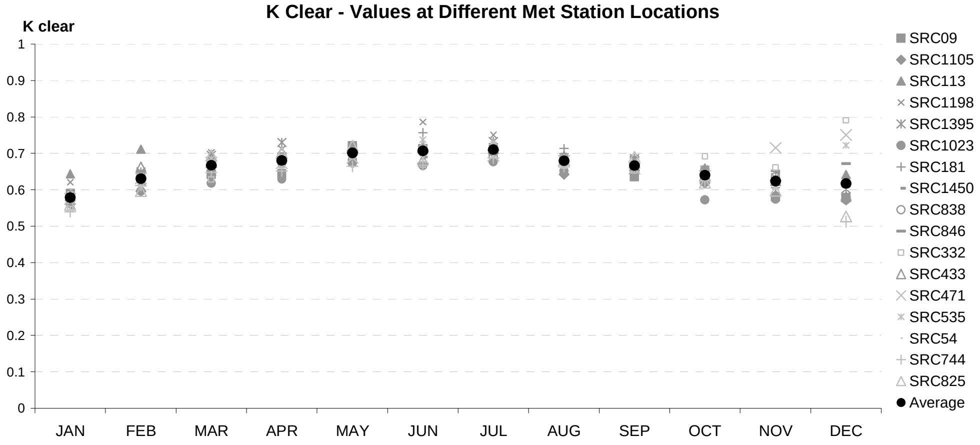


Figure 3-3: Intra-annual variability of $\overline{K}_{clear}$ at different met stations

$\overline{K}$ can be calculated from equation (3-1) now that both f_{clear} and $\overline{K}_{clear}$ are known. It can also be calculated by:

$$\overline{K} = \frac{\overline{H_h}}{\overline{H}_o} \qquad \textbf{(3-9)}$$

$\overline{H}_o$ can be calculated from equation (3-5) and averaging daily values to find the monthly value. Now values for both $\overline{K}$ and $\overline{H}_o$ can be substituted into equation (3-9) and $\overline{H}_h$, the monthly average of daily horizontal surface radiation, the parameter that is ultimately being sought, can be calculated.

3.2.1.3 Validation of the Suehrcke Method

Figure 3-4 shows data for the met station SRC535 located in North Yorkshire. The close relationship of the converted measured sunshine hours with measured solar radiation is typical for most of the locations shown in Figure 3-2 There is one location with larger than typical discrepancy (SRC554 in Nottinghamshire) and is discussed further in section 3.2.2 where the validation process is continued.

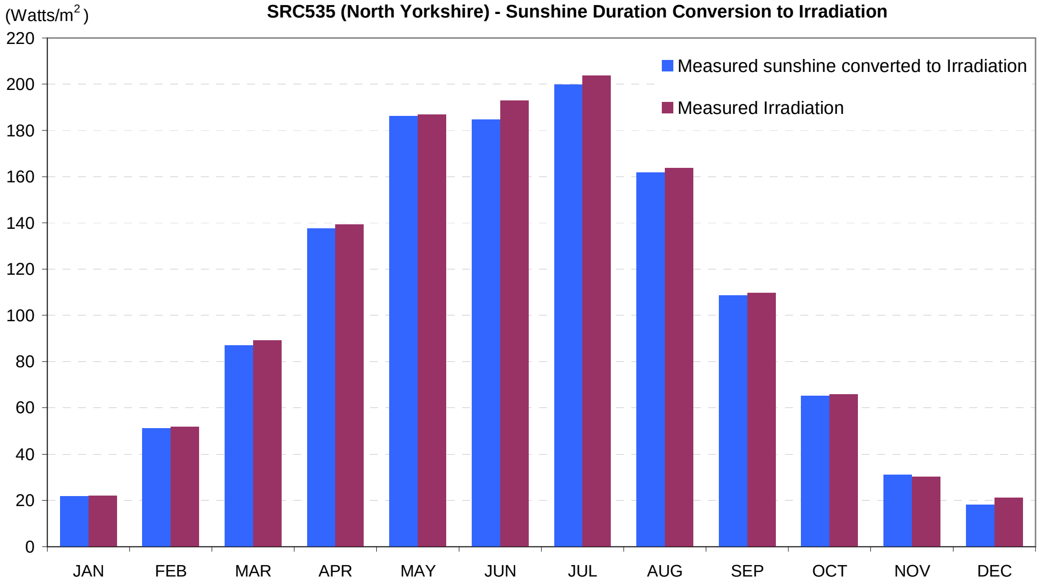


Figure 3-4: Comparison of measured sunshine hour duration converted to radiation and actual measured radiation.

3.2.1.4 Conversion of UK 5km Gridded Sunshine Duration to Solar Radiation

The 5km gridded data sets of monthly average daily sunshine duration (UK Meteorological Office 2009a) were obtained for the years from 1961 to 2005. Irregular or missing data-points were replaced by using values from adjacent cells and averaging. Sunshine duration data from each 5km cell of each month of each year were converted using the Suehrcke method with the UK monthly values of $\overline{K}_{clear}$ derived earlier. The converted monthly data between years 1961 to 1990 was averaged to create the UK baseline solar energy resource map. Figure 3-5 shows the average daily annual sunshine hour duration over the baseline period and the converted solar radiation levels. Seasonal solar radiation levels are shown in Figure A-1 in Appendix A.

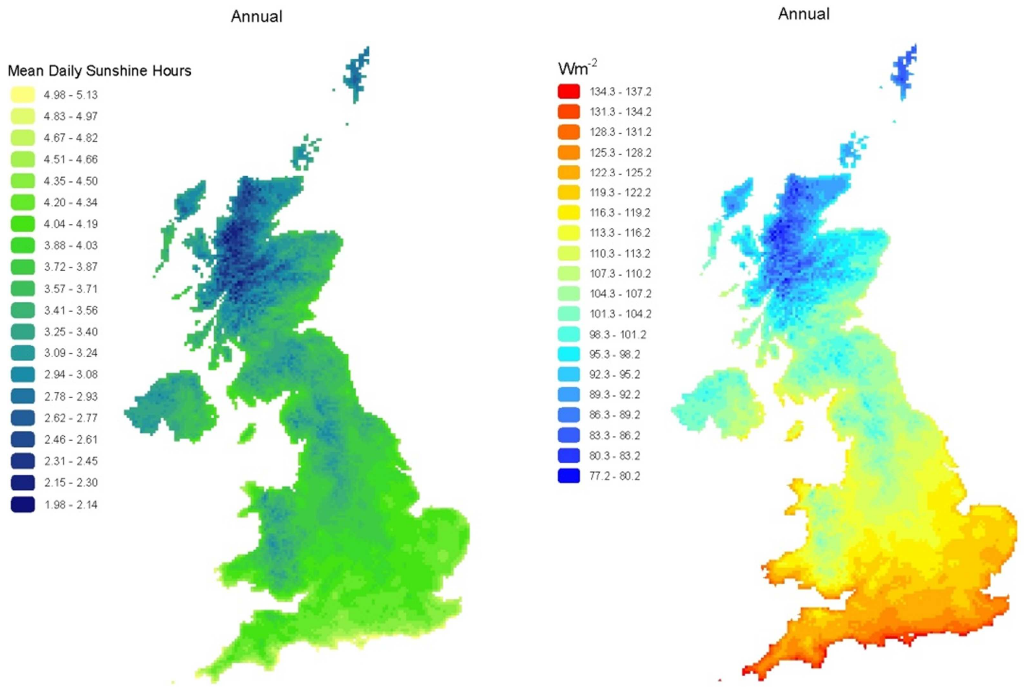


Figure 3-5: Average Daily Annual Sunshine Hours and converted Solar Radiation over the baseline time period

3.2.2 Validation of Baseline Resource

Validation of the conversion method (Suehrcke 2000) and the baseline solar radiation model were completed by comparing the derived and actual solar resource data from the eighteen weather stations (Met Office 2006) shown in Figure 3-2, with the derived solar radiation data from the gridded data sets at each station location over the same time period (1995-1999).

Figure 3-6 shows the month of June and Figure 3-7 shows the month of January for all locations. The close relationship is typical for all the other months. The higher values in the measured solar radiation for met stations SRC 554 seen in Figure 3-7 were investigated and found to be caused by erroneous spikes in the pyranometer readings throughout years three, four and five (see Figure 3-8), possibly from a defective sensor or positioning issues. All pyranometer data from the other locations had normal characteristics and were free from any similar spikes. It is unclear why the converted gridded and station sunshine duration values are slightly different at some locations. The gridded data at each station location should be generated from the station data. It is possibly due to the interpolation process used to create the gridded data, or that that not all sunshine duration data were used in the process to create the gridded data.

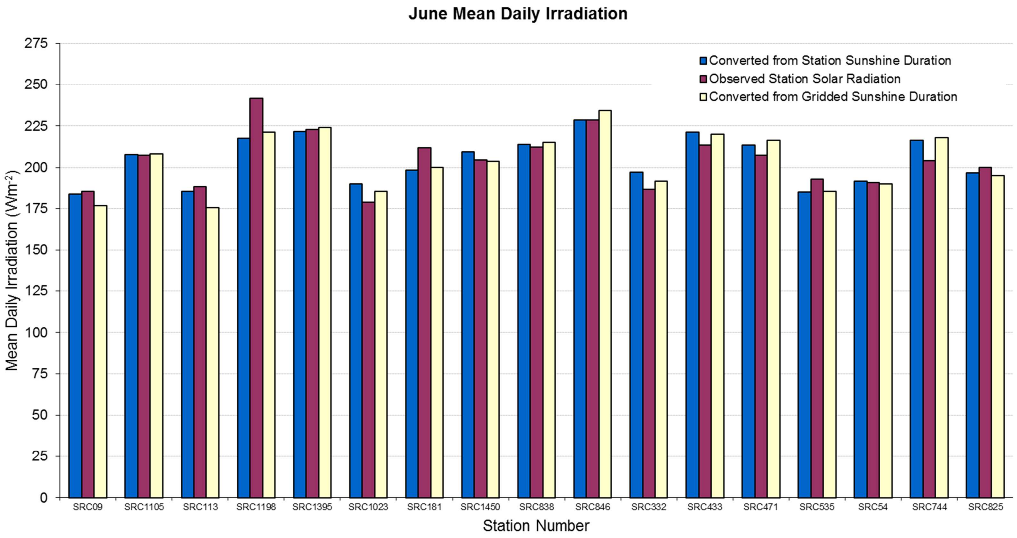


Figure 3-6: Comparison of gridded sunshine duration converted to radiation with measured radiation at all 18 locations for the month of June

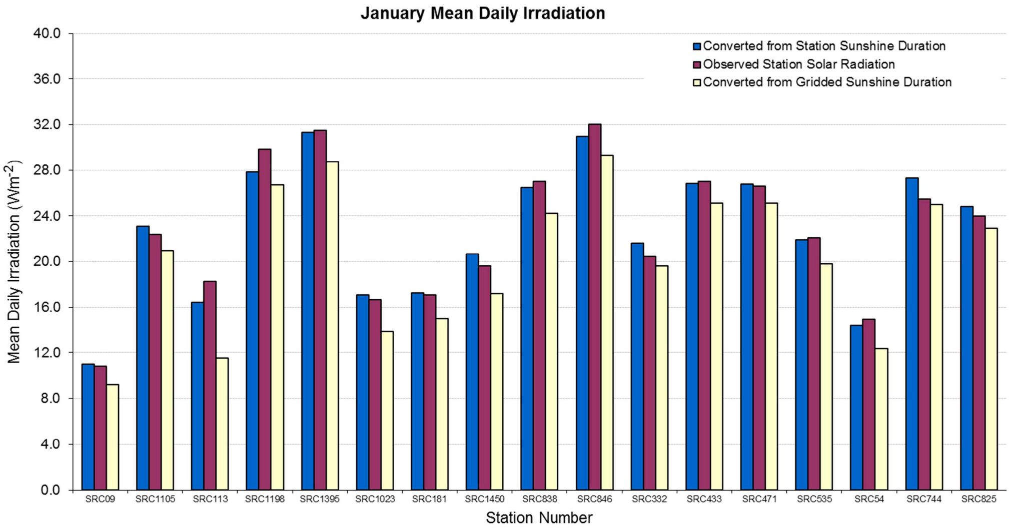


Figure 3-7: Comparison of gridded sunshine duration converted to radiation with measured radiation at all 18 locations for the month of January

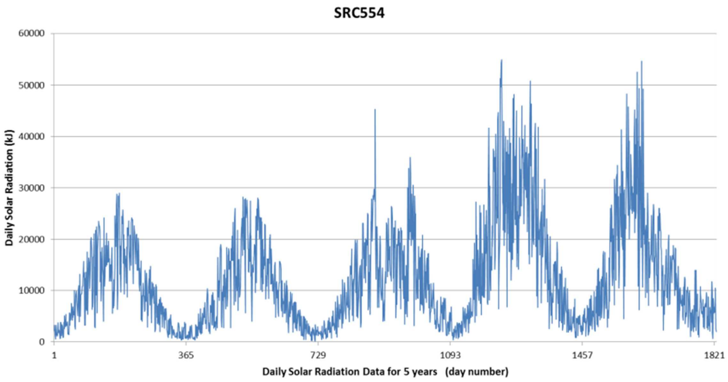


Figure 3-8: Erroneous solar radiation readings at station SRC554

Table 3-2 shows error values between actual measured solar radiation and derived solar radiation values from sunshine hours at the station and sunshine values from the gridded data for the same years and locations. SRC554 was not included in the overall average figures.

Station ID	Station			Grid		
	R^2	RMSE (W/m^2)	Mean Error (W/m^2)	R^2	RMSE (W/m^2)	Mean Error (W/m^2)
SRC09	0.9982	3.0204	0.910	0.9989	5.2747	-4.051
SRC54	0.9995	1.6028	-0.362	0.9989	5.4284	-4.820
SRC113	0.9989	2.8188	-1.771	0.9984	11.0827	-10.449
SRC181	0.9973	4.8979	-1.786	0.9993	5.5166	-4.637
SRC332	0.9967	4.5131	1.222	0.9980	3.9889	-1.441
SRC433	0.9981	3.3606	-0.866	0.9976	4.6642	-2.362
SRC471	0.9993	3.4579	0.686	0.9989	5.4326	0.342
SRC535	0.9992	2.9384	-1.931	0.9989	4.5507	-3.973
SRC554	0.9795	38.3151	-33.692	0.9724	41.0738	-36.586
SRC744	0.9991	6.0017	4.697	0.9986	7.0045	3.845
SRC825	0.9992	3.2421	-1.077	0.9984	4.5822	-3.411
SRC838	0.9996	2.5973	1.445	0.9988	3.8113	-0.528
SRC846	0.9996	2.4654	-1.838	0.9989	4.1164	-0.991
SRC1023	0.9989	6.2586	5.197	0.9985	3.1718	-0.772
SRC1105	0.9986	3.2462	1.991	0.9983	3.2062	-0.499
SRC1198	0.9994	5.1932	-3.958	0.9991	5.1856	-4.663
SRC1395	0.9986	4.5249	-2.989	0.9978	5.6710	-4.432
SRC1450	0.9999	2.9892	1.910	0.9996	3.2249	-2.916
Overall Average	**0.9988**	**3.7134**	**0.087**	**0.9986**	**5.0537**	**-2.692**

Table 3-2: Error comparisons from observed solar radiation to observed converted sunshine hours from the same met station and to converted gridded sunshine hours.

The estimated resource at selected locations was also compared with values from PV-GIS (2011), which is a GIS based computational model that derives the different solar radiation components of the chosen location. It can calculate ground radiation at an estimated optimal incline (Šúri *et al.* 2004, 2005). The PVGIS database source is satellite data covering the period 1984-2004. The accuracy of the model has an estimated cross-validation year average RMSE value of 146 Wh/m^2 (4.5%) (Šúri *et al.* 2007).

Table 3-1 shows PV-GIS values to be slightly higher, which appears to be magnified in higher latitude locations.

Horizontal Solar Radiation (W/m^2)			
	Burnett (2011)	PV-GIS (2011)	Difference
Lerwick	82.2	90.0	-7.8
Thurso	88.1	93.8	-5.7
Ullapool	89.7	96.3	-6.6
Edinburgh	98.0	100.4	-2.4
Carlisle	102.0	103.3	-1.3
Birmingham	104.9	109.6	-4.7
Southampton	117.1	118.8	-1.7

Table 3-3: Comparing average annual horizontal surface radiation with PV-GIS

The PV-GIS has an average offset of 4.3 W/m^2 (+4.4%) with a standard deviation of 2.55 W/m^2 when compared with the figures estimated in this study. It is worth noting that PV-GIS has an estimated annual average cross-validation RMSE value of 4.5% (Šúri *et al.* 2007). It is also worth noting that the described PV-GIS offset is not seen when comparing the baseline resource with actual observed values (Table 3-2).

3.2.2.1 Uncertainties

The data and method contain a number of uncertainties. The accuracy of the sunshine and radiation recordings are generally within a few percent but poor maintenance or obstructions between the instruments and the sun, such as buildings or trees can introduce errors. Systematic errors in the Campbell Stokes meters may be up to 20% at times; if there are two short bursts of bright sunshine in a close period the burns on the card can be wrongly read as one continual longer burst (Met Office 2011). The grid resolution of the gridded sunshine data does not capture all characteristics of the terrain and shaded locations and will lead to larger errors at some locations. The sunshine duration to solar radiation conversion method is an approximation and will introduce errors.

3.3 Baseline Resource on an Inclined Surface

In the previous section it was shown that resource, power density on a horizontal plane, is within about 5% of measured resource at several sites. In this section the objective is to estimate the energy yield from a representative PV system in a fixed position with a south facing incline.

The UK Baseline Solar Resource Model (as described in section 3.2) gives resource on the horizontal plane. Ideally, a solar panel would track the path of the Sun and face directly towards it at all times to maximise harvestable solar energy at all times. However, additional moving parts increase both capital and maintenance costs. Solar panels are generally on a fixed south facing incline; a fixed tilt solar panel has no moving parts and can benefit from increased reliability and low maintenance costs. Installation on south facing, or near south facing, roofs are ideal and common in the UK.

The optimal south facing inclination angle, for a fixed solar panel, is largely dependent on the latitude at the specific location. High latitude locations have a high solar declination angle resulting in solar panels requiring a higher inclination angle for optimal efficiency. The clear sky air quality and cloud cover also have an effect. A location with high levels of cloud cover may benefit from an inclination slightly closer to the horizontal plane to benefit higher levels of indirect solar radiation. One final factor that needs to be considered in calculations is that a fixed south facing incline will block some direct sunlight when close to sunrise and sunset in summer months due to the sunrise and sunset angles being reduced by the inclination.

3.3.1 Estimation of Solar Radiation Resource on an Inclined Surface

Solar radiation resource on the earth’s surface is typically measured on the horizontal plane. However, it is often necessary to obtain the resource at an incline, especially when applied to solar energy applications. It was felt necessary to modify the UK Baseline Solar Resource Model data to include resource available to a south facing inclined solar panel.

As mentioned earlier there are several commonly used empirical equations which are described in many standard solar resource textbooks and journal articles (Garg *et al.* 2000, Kalogirou 2009, Liu and Jordan 1960, Sukhatme *et al.* 1996, Twidell *et al.* 2006).

There are three radiation components making up the total solar radiation absorbed on a tilted surface: the direct, diffuse and ground reflected components (Kalogirou 2009):

$$\overline{H}_t = \overline{H}_{bt} + \overline{H}_{dt} + \overline{H}_{rt} \tag{3-10}$$

where $\overline{H}_t$ is the monthly average of daily radiation on the tilted surface (J m^{-2}), $\overline{H}_{bt}$ is the direct radiation on the tilted surface, $\overline{H}_{dt}$ is the diffuse radiation on the tilted surface, and $\overline{H}_{rt}$ is the ground reflected radiation on the tilted surface.

The ratio, or conversion factor, of monthly average daily solar radiation on the horizontal plane to monthly average of daily solar radiation on a south facing incline $\overline{r}_t$ can be calculated by (Garg *et al.* 2000):

$$\overline{r}_t = \frac{\overline{H}_t}{\overline{H}_h} = \left(1 - \frac{\overline{H}_d}{\overline{H}_h}\right)\overline{r}_b + \frac{\overline{H}_d}{\overline{H}_h}\overline{r}_d + \overline{r}_r \tag{3-11}$$

where $\overline{H}_d$ is the monthly average of daily diffuse horizontal surface radiation (J m^{-2}), $\overline{r}_b$ is the monthly average daily direct radiation conversion factor, $\overline{r}_d$ is the monthly average daily diffuse radiation conversion factor, $\overline{r}_r$ is the monthly average daily ground reflected conversion factor. The monthly average daily direct radiation conversion factor $\overline{r}_b$ can be calculated from (Sukhatme *et al.* 1996):

$$\overline{r}_b = \frac{h_{ss}\sin(\phi-\beta)\sin(\delta) + \cos(\phi-\beta)\cos(\delta)\sin(h_{ss})}{h_{ss}\sin(\phi)\sin(\delta) + \cos(\phi)\cos(\delta)\sin(h_{ss})} \tag{3-12}$$

The monthly average daily diffuse radiation conversion factor $\overline{r}_d$ can be calculated from (Sukhatme *et al.* 1996):

$$\overline{r}_d = \frac{1+\cos\beta}{2} \tag{3-13}$$

The monthly average daily ground reflected conversion factor $\bar{r}_r$ is dependent on the reflectivity, or albedo, of the surrounding ground (ρ). Assuming a typical ground albedo of 0.2 it can be calculated by (Sukhatme *et al.* 1996):

$$\bar{r}_r = \rho \frac{1 - \cos\beta}{2} \tag{3-14}$$

At this stage, the only missing component from Equation (3-10) required to convert the monthly average of daily horizontal surface radiation $\overline{H}_h$ to the monthly average of daily radiation on the tilted surface $\overline{H}_t$, is the monthly average of daily diffuse horizontal surface radiation $\overline{H}_d$. The ratio of $\overline{H}_d$ to $\overline{H}_h$ is generally known as the diffuse fraction.

The conversion process relies heavily on knowledge of the diffuse fraction at the particular location of interest, which is generally not known. There are a few empirically derived methods that attempt to estimate the diffuse fraction, one of which is a method described by Liu and Jordan (1960); their method is based on a correlation between the monthly clearness index and the diffuse fraction. The Liu and Jordan (1960) equation relates $\overline{H}_h$ and $\overline{H}_d$ to the monthly clearness index ($\overline{K}_T$):

$$\frac{\overline{H}_d}{\overline{H}_h} = 1.390 - 4.027\overline{K}_T + 5.531\overline{K}_T^{\,2} - 3.108\overline{K}_T^{\,3} \tag{3-15}$$

where

$$\overline{K}_T = \frac{\overline{H}_h}{\overline{H}_o} \tag{3-16}$$

There are four empirically derived constants in the Liu and Jordan method and they are known to be influenced by location. The Liu and Jordan empirical model had been developed for a climate different to the UK and a method to verify its accuracy for the UK climate was required.

The accuracy of Liu and Jordan's empirical equation (3-15) was assessed by comparing its estimation accuracy to actual observed diffuse and global radiation data:

$$\overline{H}_h = \overline{H}_b + \overline{H}_d \tag{3-17}$$

There are very few meteorological stations in the UK that measure both diffuse and global radiation and even fewer that have usable data over a suitable time period. Just eleven stations were identified that met the criteria of observing both global and diffuse solar radiation measurements and having a suitably long time series of recorded data. The station locations are shown in Figure 3-9.

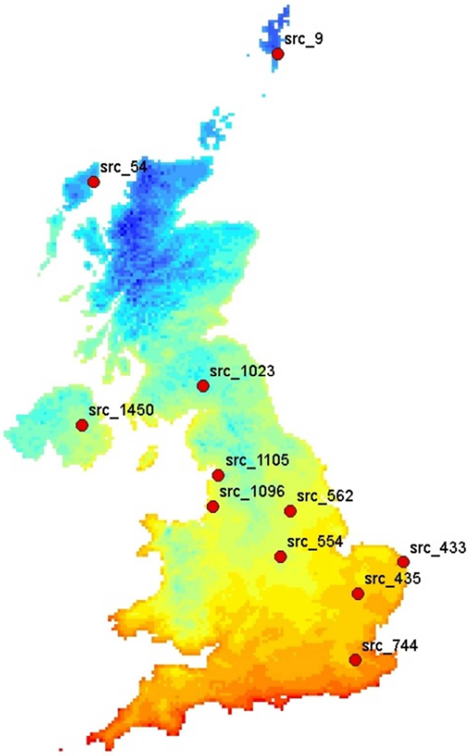


Figure 3-9: Met stations measuring both Global and Diffuse Radiation

The average monthly diffuse fractions were calculated for each of the stations using the five year time series of observed global and diffuse solar radiation data and are shown in Table 3-4. The average diffuse fractions are shown in Table 3-5, along with RMSE data and latitude and longitude correlation. The diffuse fraction is strongly positively correlated towards the north and negatively correlated towards the east, agreeing with the UK's typical weather being cloudier in more northerly and westerly locations.

	SRC09	SRC54	SRC433	SRC435	SRC554	SRC562	SRC744	SRC1023	SRC1096	SRC1105	SRC1450
Latitude	60.139	58.214	52.686	52.260	52.828	53.482	51.287	55.311	53.550	54.014	54.664
Longitude	-1.183	-6.325	1.693	0.569	-1.250	-1.007	0.451	-3.206	-2.915	-2.774	-6.224
January	0.88	0.87	0.79	0.77	0.71	0.8	0.79	0.82	0.81	0.83	0.8
February	0.8	0.79	0.74	0.75	0.67	0.77	0.74	0.77	0.78	0.8	0.76
March	0.75	0.77	0.71	0.74	0.64	0.72	0.72	0.76	0.75	0.78	0.75
April	0.7	0.71	0.63	0.67	0.64	0.7	0.64	0.71	0.67	0.71	0.68
May	0.71	0.65	0.63	0.64	0.59	0.67	0.64	0.69	0.64	0.67	0.66
June	0.71	0.72	0.65	0.66	0.58	0.67	0.64	0.7	0.67	0.7	0.68
July	0.75	0.77	0.61	0.63	0.54	0.65	0.61	0.72	0.66	0.68	0.71
August	0.74	0.78	0.6	0.63	0.54	0.62	0.6	0.73	0.66	0.7	0.72
September	0.74	0.74	0.66	0.66	0.59	0.67	0.65	0.75	0.68	0.72	0.71
October	0.79	0.76	0.68	0.68	0.61	0.7	0.72	0.77	0.73	0.75	0.74
November	0.84	0.84	0.76	0.76	0.74	0.79	0.74	0.77	0.79	0.79	0.77
December	0.9	0.88	0.8	0.81	0.71	0.81	0.83	0.81	0.85	0.84	0.81
Annual	0.78	0.77	0.69	0.7	0.63	0.71	0.69	0.75	0.72	0.75	0.73

Table 3-4: Average monthly diffuse fraction values at met stations

	Average Diffuse Fraction	Correlation with Latitude	Correlation with Longitude	RMS Diffuse Fraction	RMSE Diffuse Fraction
January	0.81	0.8	-0.41	0.81	0.0443
February	0.76	0.58	-0.38	0.76	0.0353
March	0.74	0.45	-0.48	0.74	0.0365
April	0.68	0.66	-0.61	0.68	0.0292
May	0.65	0.65	-0.24	0.65	0.0305
June	0.67	0.7	-0.51	0.67	0.0375
July	0.67	0.83	-0.67	0.67	0.0651
August	0.67	0.8	-0.73	0.67	0.0705
September	0.69	0.74	-0.57	0.69	0.0465
October	0.72	0.69	-0.49	0.72	0.0487
November	0.78	0.89	-0.47	0.78	0.0326
December	0.82	0.65	-0.27	0.82	0.0469
Annual	0.72	0.79	-0.52	0.72	0.0409

Table 3-5: Diffuse fraction correlation with latitude and longitude and error values

The actual observed average monthly clearness index ($\overline{K}_T$) values were compared to the Liu and Jordan calculated values for each of the specific met station locations The comparisons showed that the calculated diffuse fractions were significantly lower than the actual measured values, ranging from 22% too low in winter months, to 46% too low in summer months.

The average Liu and Jordan diffuse fraction values are shown in Figure 3-10; also shown are the actual station measured values and an average of the station values.

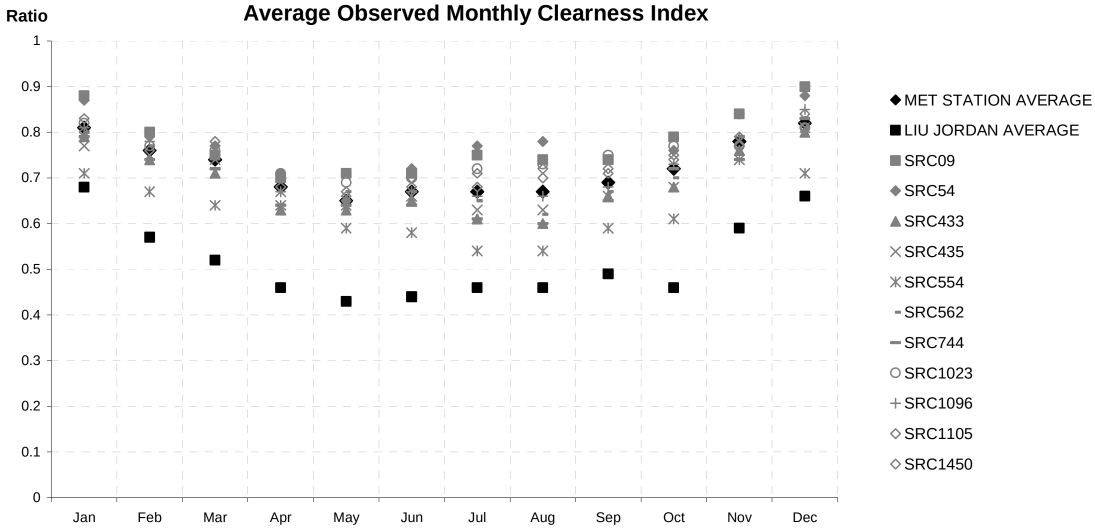


Figure 3-10: Observed Average Monthly Clearness Index Values

It was decided to use the Liu and Jordan equation (3-15), and to adjust the empirical constants for the UK climate. Five years of observed diffuse fraction data from the eleven suitable weather stations were used to generate new empirical constant values for the Liu and Jordan method. Initially, one set of optimal values were generated to suit all months, but it was found that the observed diffuse fraction over the UK varied quite significantly over the year and so empirical values for each month were generated to give greater accuracy.

The modified equation (3-18) could then be used to accurately estimate diffuse to global radiation ratios for all the 5km grid cells.

$$\frac{\overline{H}_d}{\overline{H}_h} = a - b\overline{K}_T + c\overline{K}_T^{\,2} - d\overline{K}_T^{\,3} \qquad \textbf{(3-18)}$$

where the monthly values of *a*, *b*, *c* and *d* based on actual observed diffuse and global radiation ratios are shown in Table 3-6.

Coefficient	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
a	1.516	1.559	1.581	1.570	1.569	1.578	1.562	1.559	1.563	1.609	1.565	1.538
b	3.995	3.974	3.959	3.955	3.950	3.948	3.957	3.959	3.961	3.938	3.973	3.989
c	5.408	5.548	5.555	5.560	5.564	5.565	5.560	5.559	5.557	5.568	5.548	5.541
d	3.106	3.103	3.099	3.096	3.094	3.094	3.096	3.097	3.098	3.093	3.103	3.105

Table 3-6: Optimal empirical constant values for the UK

The use of the new values in Table 3-6 with equation (3-18) move the Liu Jordan average up to align exactly with the met station observed average diffuse fraction values.

3.3.1.1 Optimal Inclination Angle

Figure 3-11 shows monthly optimal inclination angles calculated at two locations: The Shetland Islands, in the far north and the South East Coast of England. Averaged optimal angles for the UK as a whole are also shown. The higher optimal inclination angles for Shetland in the far north is clearly visible for non-winter months but in December and January, the higher cloud cover resulting higher diffuse fraction results in a lower than expected optimal inclination angle.

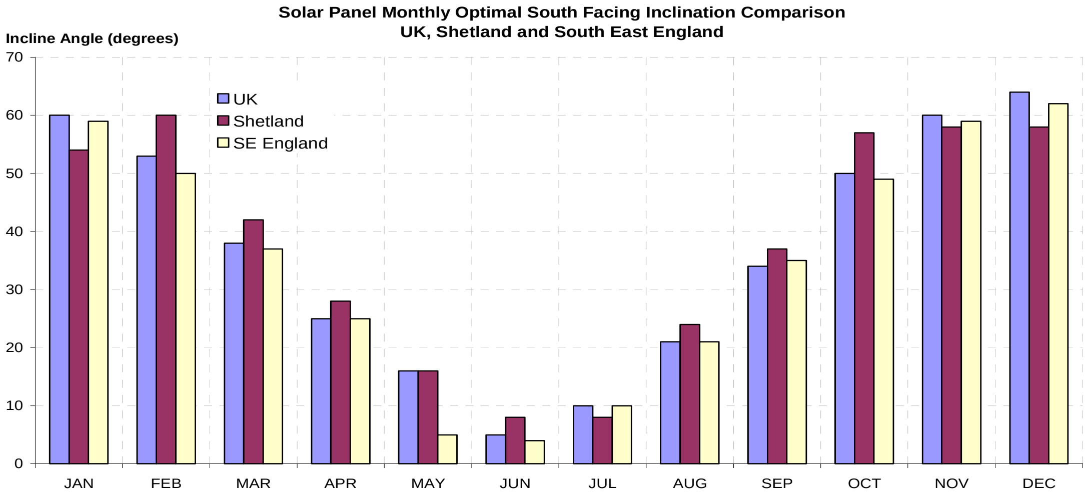


Figure 3-11: Monthly optimal south facing incline at extreme latitudes of the UK and for the UK in general.

The benefit of an inclination angle can clearly be seen in Figure 3-12. The angle is shown in degrees. The gain is shown on the same scale as the angle and is divided by ten to get the correct value. Summer months do not benefit greatly but the poor resource in winter months can be substantially increased with an optimal inclination angle. An annual gain of 9% was estimated by using monthly optimal inclination angles rather than a horizontal plane.

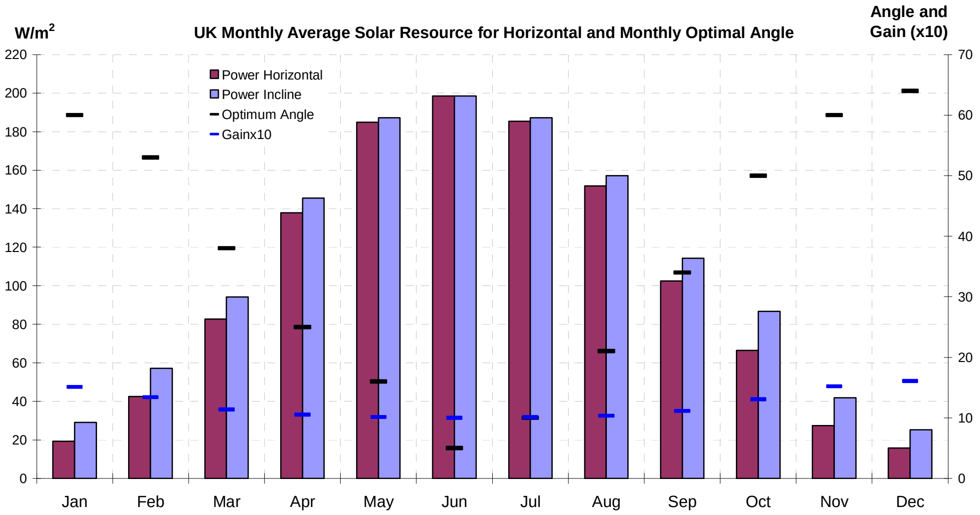


Figure 3-12: Monthly optimal inclination angles and gain from the horizontal plane for the UK

This study assumes that the majority of solar PV installations do not have active tracking mechanisms and so are lower cost installations with a permanently fixed incline. The study will also assume that all installations are south facing with an inclination angle of 28° which was found to be the optimal angle for maximum gain for the UK as a whole (see Figure A-2 in the Appendix). In extreme UK latitudes the optimal fixed angle varied from 27° in the extreme south, to 29° in the extreme north.

Figure 3-13 shows how a fixed incline of 28^{o} compares with resource on the horizontal plane. In winter months, when solar resource is poor, the incline can significantly increase the available resource by up to 61% in December. However, in summer months, the benefit of the incline reduces due to the higher Sun declination and the south facing incline blocking solar radiation resource in early morning and late evening.

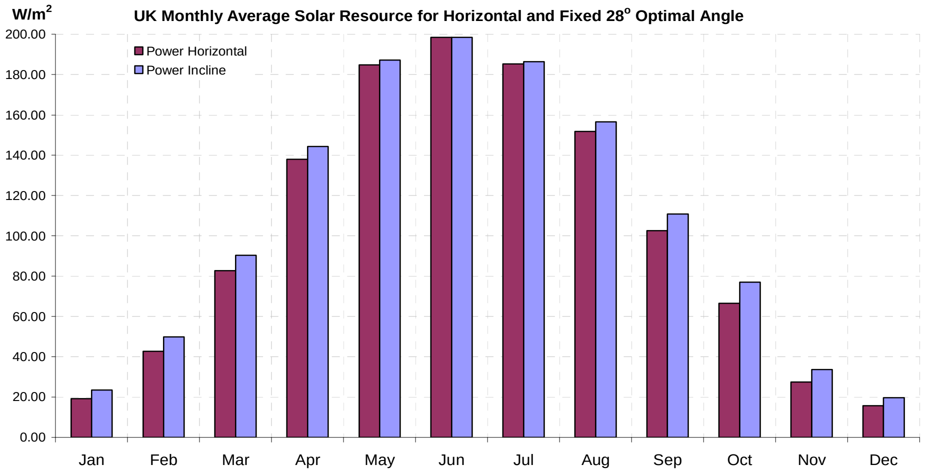


Figure 3-13: Comparison of Resource from Horizontal Plane and South Facing Fixed Incline of 28^{o}

The derived optimal angles (27^o to 29^o) appear to be on the low side when compared to some other figures. PV-GIS (2011) estimate optimal angles to be in the region of 35^o to 39^o over the full latitude range of the UK. However, it may be the observed relatively high proportion of cloud cover over the UK that has resulted in the calculations in this report being relatively lower than the PVGIS values. The diffuse component is largely the main source of error in solar radiation models (Šúri *et al.* 2004) and it is possible that it is a large diffuse error in the PV-GIS calculations over the UK that has caused the difference in solar radiation resource, optimal angle and optimal angle gain.

Returning to the earlier comparison of PV-GIS measurements (Table 3-3) and shown previously. Here in Table 3-7 are further comparisons of the same locations showing the estimated optimal inclination angle.

Optimal incline solar resource comparison with PV-GIS						
Location	Horizontal (W/m^2)		Optimal Incline (W/m^2)		Optimal Incline Gain (%)	
	Burnett (2011)	PV-GIS (2011)	Burnett (2011)	PV-GIS (2011)	Burnett (2011)	PV-GIS (2011)
Lerwick	82.2	90.0	87.9	105.0	6.9	16.7
Thurso	88.1	93.8	95.1	110.0	7.9	17.3
Ullapool	89.7	96.3	95.8	112.1	6.8	16.4
Edinburgh	98.0	100.4	105.8	117.1	8	16.6
Carlisle	102.0	103.3	109.8	120.4	7.6	16.6
Birmingham	104.9	109.6	111.5	125.4	6.3	14.4
Southampton	117.1	118.8	125.1	136.7	6.8	15.1

Table 3-7: Comparing average annual optimal incline solar resource with PV-GIS

The PV-GIS optimal angles at the locations range between 36^o to 39^o compared to estimations of 27^o to 29^o in this study. The average PV-GIS inclination angle gain is 16.2%, compared to 7.2% in this study. There is a high degree of confidence of the figures derived in this study. They are derived using actual observed diffuse and global radiation values from several UK locations. The lower optimal angle and gain values estimated in this study are thought to be due to the observed solar radiation data having a larger than expected diffuse to global solar radiation ratio (less sunny). This reduces the benefit (and gain) of an incline: a solar panel is more efficient on the horizontal plane when there are periods of obstructed daylight; therefore, a location with higher annual proportions of obstructed sunlight than another location on the same latitude would be more optimal at a lesser inclination angle.

There is other evidence of differing optimal angle calculations. For example, Li *et al.* (2007) studied the optimal angle for Hong Kong at latitude of 36^o. Their method used radiation observations over a year in ten minute time samples. The outcome was an optimal inclination angle of 20^o. PVGIS explored locations in Europe with similar latitudes to Hong Kong, and all optimal inclination angles were returned to be in the region of 31° which is considerably higher than the calculations based on actual observations. Some methods of estimating optimal inclination angles appear to use global models which depending heavily on latitude and may not take localised weather patterns into account, Lorenzo (2005) for example.

3.4 Solar PV Electricity Generation

3.4.1 PV System Particulars

To accurately estimate the output of a PV system it is necessary to know its performance characteristics. The ratio of the power generated to the solar irradiation incident is defined as the efficiency of the system. The instantaneous energy generated from a PV system depends on the input solar resource and several other variables including: system operating temperature; air mass; solar cell, module and inverter technology and operating characteristics; all of which affect the overall efficiency of the system.

There are several types of solar PV systems with different solar cell, module, and inverter technologies; all of which result in a large spread of potential system costs and efficiencies. This study uses the characteristics of a commercially available PV module to explore the potential PV output resource. The key parameters of the chosen PV panel are shown in Table 3-8. The efficiency of this particular solar PV panel, at 14.1%, is a little higher than the mid end of current commercially available panels, but much lower than the most efficient but more expensive commercially available panels that can reach efficiencies of around 20%. An efficiency of 95% is assumed for the inverter.

SUNTECH STP180S-24-Ad	
Area (m^2)	1.28
Power (W/m^2)	141
Efficiency	14.1
Technology	Polycrystalline
Peak Output (W)	295

Table 3-8: Key characteristics of commercially available solar PV panel (Solar Access 2011)

3.4.2 Technology Deployment

It is difficult to predict location and size of future UK PV installation deployment. However, it can be assumed that more southerly locations - with higher solar resource - will be more popular. Locations with higher population density can also be assumed to have more rooftop

PV installations. Both assumptions lead to there being a larger weighting of PV technology in more southerly locations such as the South of England.

3.4.2.1 UK Geographic Regions

The UK solar resource varies quite considerably, more southerly UK latitudes have more available resource than more northerly locations. The majority of present and future solar PV installations will be weighted towards the south as they will be more economically viable and reach grid parity sooner than more northerly locations, but there will be installations in higher latitude locations, especially in more populated locations.

For this study the UK has been split into six geographical regions with relatively similar solar resource as shown in Figure 3-14. A weighting of the proportion of UK solar PV resource has been estimated for each region. Technology, resource and an average UK levelised cost of Solar PV can then be more easily estimated. The effect of climate change can be assessed incorporating regional differences. The weighted regional resource characteristics are used to generate baseline solar PV output resource values for the UK.

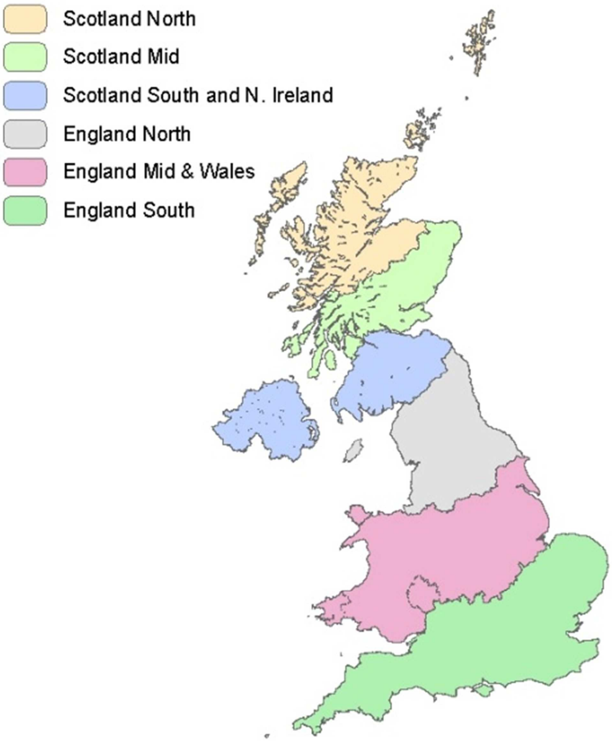


Figure 3-14: Solar Resource Regions

The assumed proportions of installed solar PV in each region of Figure 3-14 are shown in Table 3-9.

Regional Proportion of Solar Resource Regions and Proportions of assumed Solar PV Resource		
Region	Proportion of Total Area	Solar PV Resource Weighting
UK and Northern Ireland (N.I.)	100%	Not weighted
Scotland North	15.4%	0.05
Scotland Mid	10.8%	0.12
Scotland South and N.I.	13.1%	0.08
England North	12.7%	0.15
England Mid and Wales	22.8%	0.25
England South	25.2%	0.35

Table 3-9: Solar PV Assumed Regions and Proportions

3.4.2.2 Solar Baseline Resource in UK Geographic Regions

Table 3-10 and Table 3-11 show the regional averaged baseline solar resource for each of the regions for a horizontal plane and a fixed 28^{o}south facing incline. Also shown at the bottom of each are the weighted values for UK and Northern Ireland. Note these values are higher than the un-weighted UK and NI values as they assume the higher proportions of installed solar PV in more southerly regions as discussed in section 3.4.2.1.

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Ann
Scotland North	10.7	34.7	69.9	125.8	167.7	177.9	156.3	128.0	80.8	48.8	16.1	7.4	85.3
Scotland Mid	14.0	37.3	75.2	132.5	174.7	188.1	173.5	139.0	89.6	55.5	21.2	10.5	92.6
Scotland South & N .I.	17.5	40.7	78.7	136.7	180.7	191.4	175.0	142.6	95.0	60.3	25.4	13.7	96.5
England North	18.8	40.9	80.7	133.2	182.8	197.2	183.2	150.0	100.8	64.7	27.0	15.4	99.5
England Mid & Wales	22.0	44.7	86.3	139.3	189.2	203.4	193.7	159.0	109.7	72.4	30.8	18.4	105.7
England South	25.1	49.5	93.3	148.9	198.2	215.2	206.7	170.8	119.7	80.4	35.2	21.7	113.7
UK & N.I.	19.2	42.6	82.7	137.9	184.8	198.5	185.3	151.8	102.6	66.4	27.4	15.7	101.2
UK & N.I. Weighted	20.7	44.1	85.2	140.0	187.9	202.5	190.9	156.5	106.8	69.9	29.5	17.2	104.2

Table 3-10: UK Baseline Solar Resource for Horizontal plane in W/m^2

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Ann
Scotland North	13.6	46.4	79.8	133.8	168.7	174.8	154.7	131.8	88.8	60.3	20.5	9.3	90.2
Scotland Mid	19.3	48.9	85.9	140.8	175.8	184.4	171.9	143.8	99.4	69.4	29.8	14.9	98.7
Scotland South & N .I.	24.3	52.1	89.1	144.8	181.0	187.6	173.0	146.8	105.1	74.7	35.8	19.5	102.8
England North	25.9	51.1	91.1	140.0	182.9	193.3	181.4	154.7	112.0	80.7	37.5	22.4	106.1
England Mid & Wales	29.6	54.9	96.8	145.8	189.1	198.8	191.5	163.7	121.9	89.7	41.5	25.7	112.4
England South	33.9	61.0	105.1	156.2	197.9	209.4	204.1	175.9	133.5	100.1	47.8	30.6	121.3
UK & N.I.	26.0	53.7	93.4	145.3	185.0	194.1	183.2	156.4	113.9	82.5	37.3	22.1	107.8
UK & N.I. Weighted	28.1	55.1	96.1	147.3	188.0	197.9	188.7	161.3	118.8	86.9	40.2	24.3	111.0

Table 3-11: UK Baseline Solar Resource for a Fixed 28° South Facing Incline in W/m^2

Table 3-12 shows the regional averaged baseline solar PV output each of the regions, and both un-weighted and weighted UK solar PV output capacity factor values for the UK and Northern Ireland for a fixed 28^o south facing incline. It shows the intra-annual variability between different regions, and the increase in overall resource when the resource has a regional weighting.

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Ann
Scotland North	1.6	5.6	9.7	16.2	20.5	21.3	18.8	16.0	10.7	7.3	2.5	1.1	11.0
Scotland Mid	2.4	6.0	10.4	17.1	21.3	22.4	20.9	17.5	12.1	8.4	3.6	1.8	12.0
Scotland South & N .I.	3.0	6.4	10.8	17.6	22.0	22.8	21.0	17.8	12.8	9.1	4.3	2.4	12.5
England North	3.1	6.2	11.1	17.0	22.2	23.5	22.0	18.8	13.6	9.8	4.5	2.7	12.9
England Mid & Wales	3.6	6.7	11.8	17.7	23.0	24.2	23.3	19.9	14.8	10.9	5.0	3.1	13.6
England South	4.2	7.5	12.8	19.0	24.1	25.4	24.8	21.3	16.2	12.2	5.8	3.7	14.7
UK & NI Unweighted	3.1	6.5	11.4	17.6	22.5	23.6	22.3	19.0	13.8	10	4.5	2.7	13.1
UK & NI Weighted	3.5	6.7	11.7	17.9	22.8	24	22.9	19.6	14.4	10.6	4.9	3.0	13.5

Table 3-12: Regional Baseline Solar PV Capacity Factor (%) for Fixed 28° South Facing Incline

3.4.2.3 Capacity Factor

The term 'capacity factor' is used extensively throughout this study. The capacity factor is the ratio of actual power output from a power plant over the output if it had been continually operating at full capacity throughout a period of time (often a year). Capacity factor is often expressed as a percentage.

Figure 3-15 shows the estimated annual baseline Solar PV output capacity factor values for the UK and Northern Ireland.

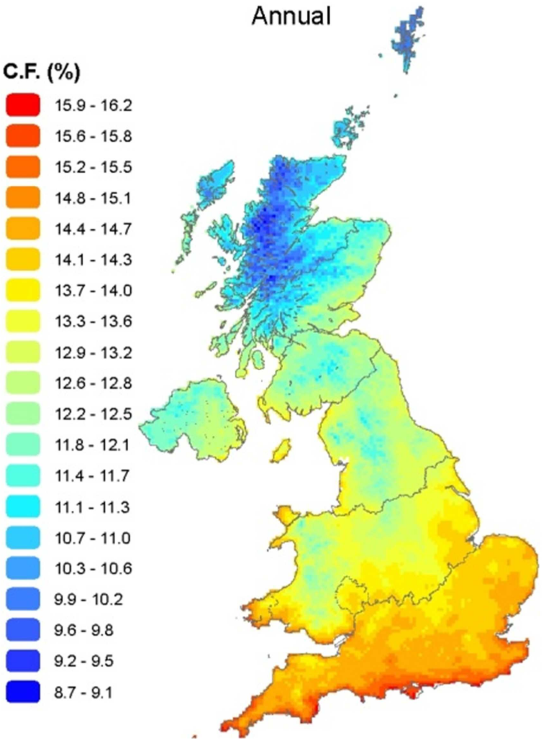


Figure 3-15: Baseline Solar PV Capacity Factor Values

3.5 Climate Change Impact

3.5.1 UKCP09 Probabilistic Projections

The UKCP09 probabilistic climate change projections were used to explore the climate change impact on the UK’s solar resource. The variable ‘total downward surface shortwave flux’ is one of sixteen UKCP09 probabilistic output variables over land and is the measure of horizontal solar radiation.

Two thirty year future time periods were explored: 2050s (2040 to 2069), 2080s (2070 to 2099). Low, medium and high scenarios and probabilistic data at 50%, 10%, and 90% were extracted from the UKCP09 projections. The settings for extraction were as follows:

Climate Change Type:	Future Climate Change Only
Output Variable:	Change in downward surface shortwave flux (Wm^{-2})
Emissions Scenario:	2040-69 (2050s), 2070-99 (2080s)
Temporal Average:	Monthly
Probability Levels:	50% (10%, 90%)

UKCIP09 ‘Change in total downward surface shortwave flux (Wm^{-2})’ projection data was downloaded via the UKCP09 user interface for medium and high emissions scenarios for 50%, 10% and 90% probability levels.

Figure 3-16 shows projections for surface radiation in the 2050s medium scenario with a probability of 50% for summer months (June, July, August). The data shows relative change from baseline with units in Wm^{-2}. It indicates significant solar radiation increases in the south-west, the increases become less significant travelling further north with much of Scotland showing little change from baseline except in the far north and westerly regions in the Highlands of Scotland, where there are slight decreases in radiation.

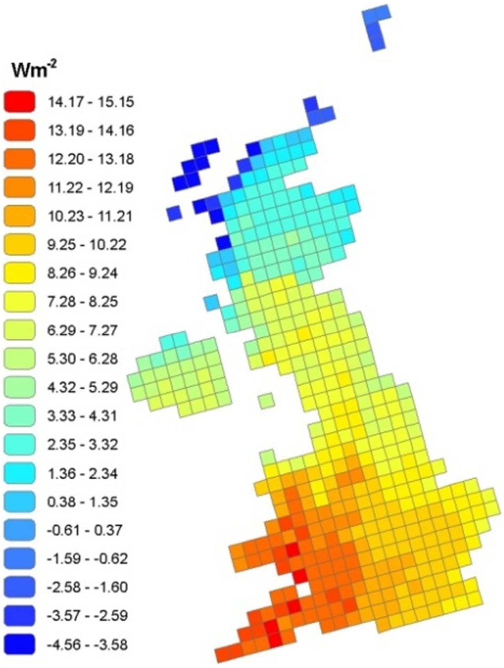


Figure 3-16: Data from UKCP09 projections showing change in downward short wave surface radiation for 2050s summer months, medium scenario 50% probability

The projected average percentage change of horizontal surface solar irradiation can be calculated for the 2050s and 2080s by projecting the UKCP09 climate change anomalies onto the baseline solar radiation model. Figure 3-17 shows the baseline resource for summer months (left); the UKCP09 2050s medium scenario relative change from baseline with 50% probability (middle); and the resulting percentage change from baseline (right). It shows similar characteristics as previously discussed for Figure 3-16 but in percentage terms the impact climate change has on the resource is more evident.

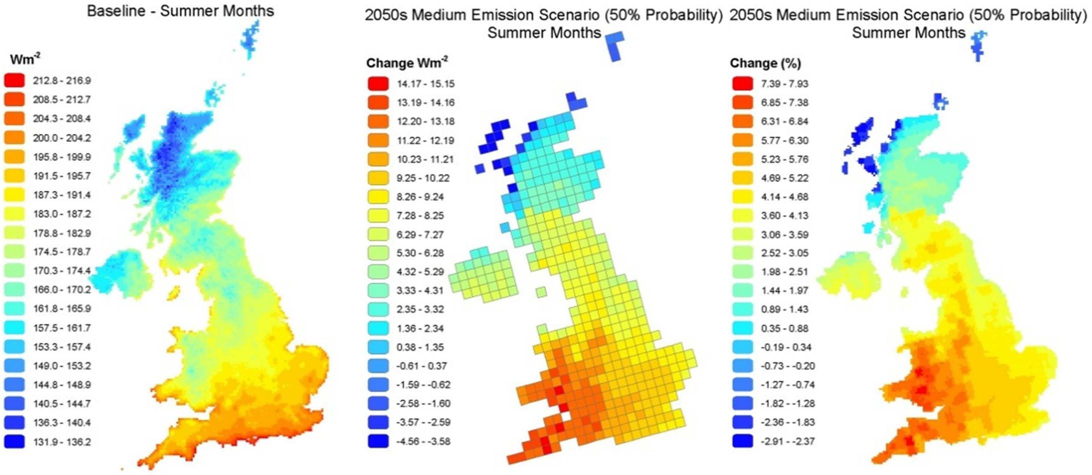


Figure 3-17: Summer solar resource: baseline; 2050s change in wm^{-2}; and percentage change from baseline

Figure 3-18 shows the 10%, 90% and 50% probabilities for 2050s summer months medium scenario. The 50% probability distribution shows the central estimate, the 10% is very likely to be exceeded and the 90% is very unlikely to be exceeded. The 50% figure is the same data as shown in Figure 3-17 on the right but is shown over a wider range to incorporate the 10% and 90% distributions and, therefore has less resolution. Further seasonal and annual results for the 2050s and 2080s medium emissions projections are shown in Figures A-3 and A-4, in the Appendix. They show increases in solar resource in spring, summer and autumn especially in more southerly locations and reductions in winter months UK wide.

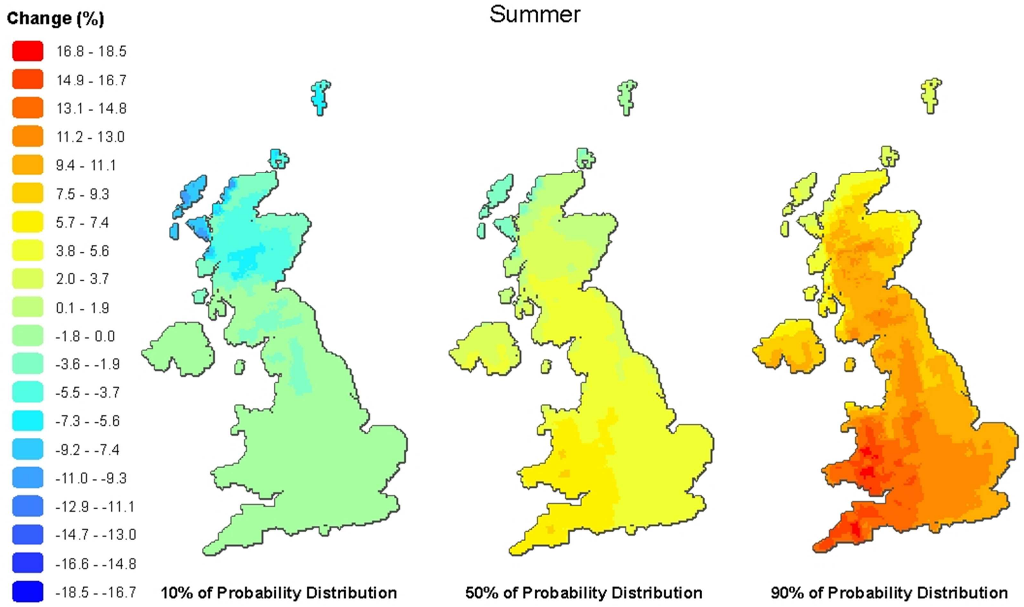


Figure 3-18: Summer solar percentage change from baseline for 2050s medium scenario 50% (10%, 90%) probabilities

3.5.1.1 Solar Regional Weighted Projections

The next stage is to apply the projection scenarios to the weighted UK solar regions discussed in 3.4.2.1, explore how each region is affected by the climate projection scenarios, and finally, look at the effect of climate change on the UK Baseline Solar PV output. The impacts on levelised costs and the financial risk are explained in chapter 7.

The following charts show how the UK Baseline Solar PV resource each region will be affected by climate change. The chart in Figure 3-19 shows the average regional change in percentage from baseline and is applicable to both the solar resource and the solar PV output capacity factor. The figures are good for seeing the actual extent of change relative to each individual month.

Figure 3-19 clearly shows the reduction of solar resource over winter months in all regions, this is most apparent in more northerly regions. Nearly all regions show solar resource increases in summer months, especially in more south and south westerly regions. Summer months in north Scotland show a relatively flat response, just slightly above the zero mark for much of the months between Spring and Autumn.

Figure A-6 in Appendix A shows the same as Figure 3-19 but the change is shown in absolute values (Wm^{-2}). This is good for seeing the change in real terms; however, the detail in winter months is reduced due to the much smaller baseline resource relative to summer months.

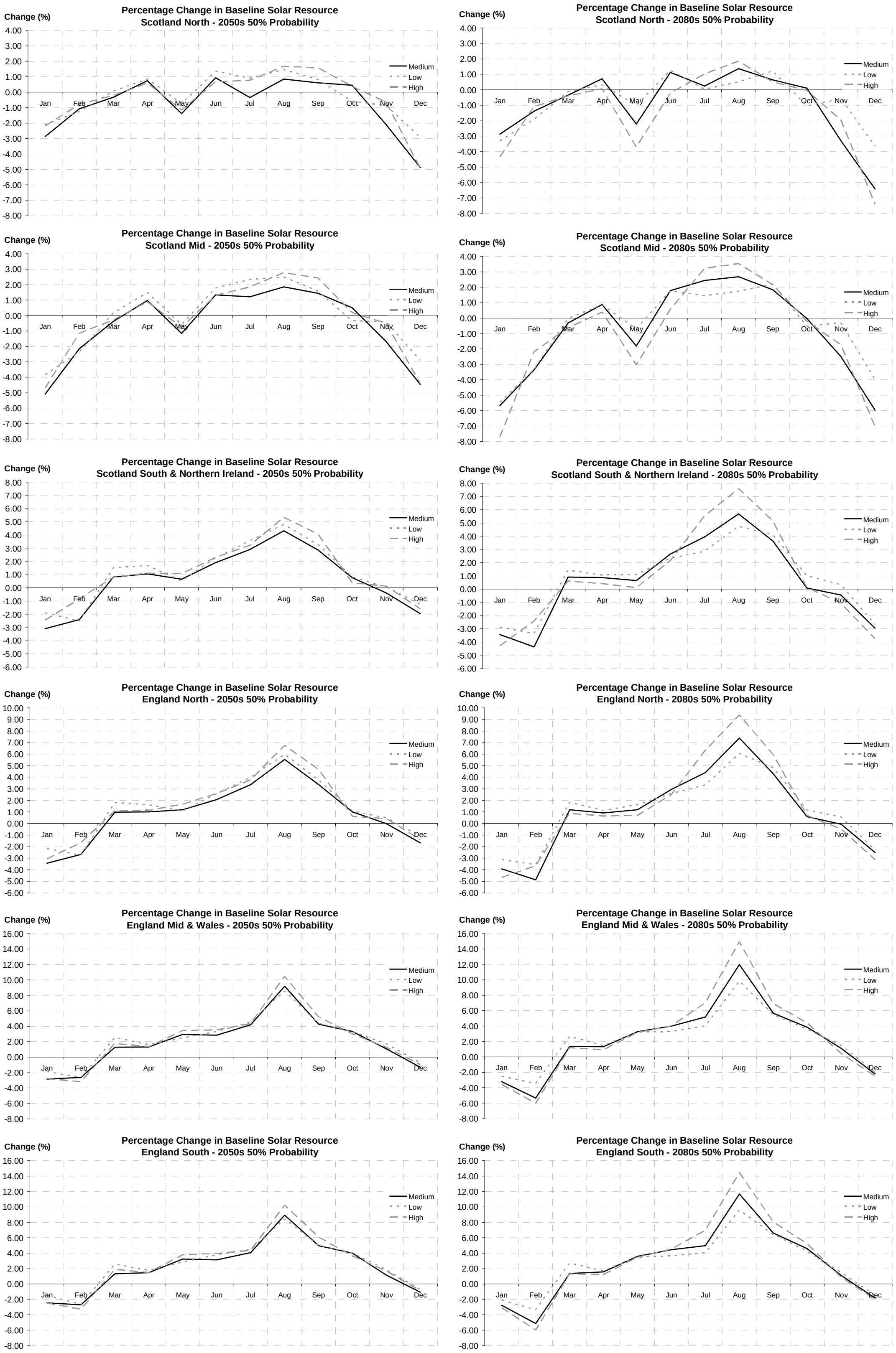


Figure 3-19: Regional Average Percentage Change from Baseline for the 2050s and 2080s

Table 3-13 shows the weighted projected percentage change from baseline of the UK solar resource with a 50% probability level. The percentage change values are applicable for both input solar resource and the solar PV output capacity factor, and therefore is the percentage change a solar PV system will experience for the future projection scenarios.

The 2080s high emissions scenario shows the most extreme changes, with an annual increase of 4.8% (-1.1%, 11.1%), a huge increase of 11.7% (-1.3%, 25.1) in August, and the largest decrease of -3.9% (-14.1, 5.3) in January. The other scenarios show the same characteristics as the 2080s high emissions scenarios but to a lesser extent; the 2050s high emissions scenario shows roughly the same characteristics but reduced by around 18% and the 2050s medium emissions also showing the same characteristics but reduced by around 33%.

Probabilistic UK Weighted Percentage Change from Baseline of Solar Resource (%)													
Scenario	Prob	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Ann
2050 Medium	10%	-10.9	-9.4	-4.8	-3.9	-3.7	-3.8	-5.0	-1.2	-3.4	-2.2	-4.6	-6.3	-0.7
	50%	-3.0	-2.5	1.0	1.2	2.0	2.5	3.4	7.1	3.9	2.7	0.5	-1.6	3.2
	90%	4.5	4.0	6.7	6.4	7.9	9.1	12.7	15.8	11.8	8.1	5.7	3.0	7.4
2050 Low	10%	-9.6	-9.0	-4.3	-3.1	-3.9	-3.2	-4.2	-2.0	-2.6	-1.8	-3.6	-6.0	-0.5
	50%	-1.9	-2.6	2.0	1.6	1.8	3.0	4.0	6.9	4.06	2.6	1.2	-1.0	3.6
	90%	5.4	3.6	8.3	6.4	7.6	9.5	12.9	16.2	11.2	7.4	6.2	3.9	8.0
2050 High	10%	-10.5	-9.3	-4.6	-3.7	-3.7	-4.0	-5.6	-0.6	-2.5	-2.4	-4.2	-5.5	-0.4
	50%	-2.8	-2.5	1.3	1.3	2.5	3.1	3.8	8.3	5.0	2.4	1.0	-1.4	3.9
	90%	4.4	4.1	7.3	6.3	8.9	10.5	14.2	18.0	13.3	7.7	6.4	2.8	8.6
2080 Medium	10%	-12.9	-13.7	-5.3	-4.4	-4.3	-4.4	-5.5	-0.8	-2.5	-2.3	-5.1	-7.1	-0.5
	50%	-3.3	-4.8	1.1	1.2	2.1	3.5	4.4	9.3	5.1	2.9	0.4	-2.5	4.2
	90%	5.4	3.6	7.2	6.8	8.9	11.5	15.4	19.9	13.7	9.0	6.0	2.2	9.1
2080 Low	10%	-11.1	-11.1	-3.8	-3.6	-3.9	-3.5	-5.3	-1.5	-2.4	-2.0	-4.2	-7.4	-0.6
	50%	-2.7	-3.3	2.1	1.4	2.3	3.0	3.4	7.6	5.2	2.8	1.1	-2.0	3.9
	90%	5.2	4.0	7.9	6.4	8.7	9.8	13.2	17.4	13.2	8.1	6.5	3.4	8.7
2080 High	10%	-14.1	-14.0	-4.9	-5.0	-5.7	-4.9	-6.1	-1.3	-3.5	-2.7	-5.4	-7.8	-1.1
	50%	-3.9	-4.8	0.9	0.9	1.7	3.3	6.1	11.7	6.4	3.3	0.1	-2.9	4.8
	90%	5.3	4.0	6.8	6.7	9.8	12.0	19.6	25.1	17.4	10.4	5.8	2.1	11.1

Table 3-13: UK Weighted Solar Resource Projected Percentage Change from Baseline

3.6 Solar Energy Summary

Accurate estimations of mean monthly solar radiation resource have been generated from mean monthly sunshine duration measurement data using a method described by Suehrcke (2000). A baseline model of present climate UK solar radiation has been developed and validated. A baseline model of solar PV output on the horizontal plane and at an optimal south facing inclination has also been developed.

UKCP09 climate change projections have been used to show relative climate change impact for a baseline at a national and regional scale. All ranges have been examined and one is presented here. By the 2050s, under a ‘medium emissions’ scenario, summer months show solar radiation increases of up to 7.9% (within a range of -0.2% to 18.1%) in the south west, these reduce further north with decreases of up to -2.9% (within a range of -10.8% to 1.8%) in the north of Scotland. Winter months show a reduction throughout the UK with extremes of -7.6% (within a range of -25.2% to 10.1%) in mid-west Scotland. This shows that most parts of southern UK will get sunnier and benefit from increased solar energy resource in summer, while the relatively poor resources in the north will decrease slightly. All regions in winter will have increased cloud cover and slightly reduced solar energy resource. The UK will see an overall annual increase of 2.6% (within a range of -1.1% to 6.5%), which is positive news for the viability of solar technologies, particularly in southern regions and would correlate well with increased use of air cooling systems due to the increased temperatures. However, the resource will be more seasonally variable and regional resource differences will be further reinforced. See Burnett *et al.* (2010) for additional information on climate change and solar resource.

Table 3-14 shows the solar PV capacity factor values estimated in this chapter. These figures are used in chapters 7 and 8 when calculating levelised cost values for solar PV.

Technology	Climate Scenario						
	Baseline	2050 10%	2050 50%	2050 90%	2080 10%	2080 50%	2080 90%
Solar PV	13.5	13.4	13.9	14.5	13.4	14.2	15.0

Table 3-14: Solar PV capacity factor values

The mean error of the gridded horizontal solar radiation model is in the region of -2.7 W/m^2 (roughly -2.7%) with a RMSE error of 5.1 W/m^2 (roughly 5.1%), when compared to solar radiation observations from several measurement stations. The accuracy of the observations used for the validations are generally within a few percent. A further comparison with PVGIS data showed the data to have an average offset of -4.3 W/m^2 (-4.4%).

The optimal south facing inclination model shows large differences in optimal angle when compared with PVGIS estimations (this study: 28^o; PVGIS: 37^o) and gain values (this study: 7.2%; PVGIS: 16.2%). There is a high degree of confidence in the estimations in this study due to the inclusion of actual observed data. Further work to explore the optimal inclination angle for the UK is recommended and included in section 9.5 ‘Recommendations for Further Work’.

4 Onshore Wind Power

4.1 Introduction

The main objective of this chapter is to assess the baseline onshore wind resource of the UK and investigate the impact climate change could have on the resource. It uses observed monthly average wind speeds to explore the present (baseline) wind speed and energy characteristics, and wind output from the Hadley Centre RCM HadRM3 (Met Office 2008) model to assess the potential future change from baseline.

The yellow blocks in the thesis flowchart (Figure 4-1) signify the areas of the thesis connected with this chapter.

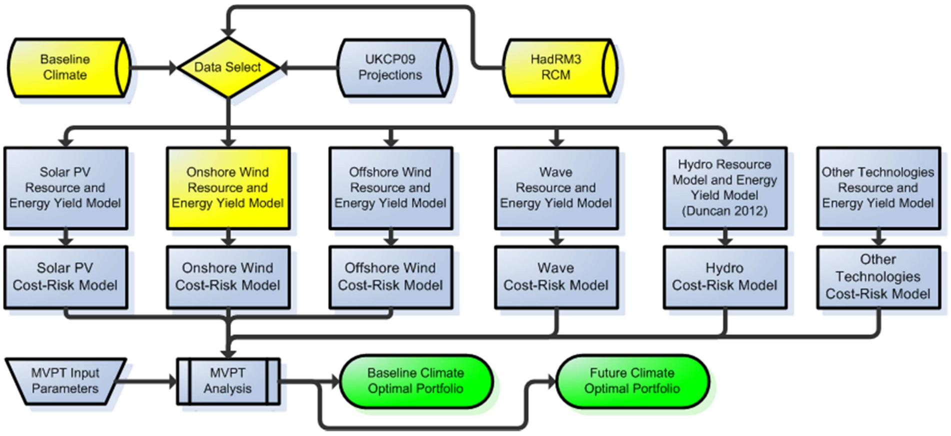


Figure 4-1: Thesis flowchart and onshore wind resource blocks

4.1.1 Chapter Overview

Wind speed data is measured at many onshore weather stations over the UK and many have several decades of recorded data. The Met Office have used much of the UK’s observed wind data to develop annual monthly average 5km x 5km gridded data sets of onshore wind speed data over the UK. The gridded data sets cover in excess of 30 years and were used as the main source of observed wind data over the period 1961 to 1990. The wind speed data was converted in two different ways – to generate a baseline wind speed model and to generate a baseline wind energy resource model.

To generate the baseline wind speed model the gridded wind speed data was converted from its observed height of 10m to the hub height of a typical wind turbine hub height (80m), each month was then averaged over the baseline period. To generate the baseline wind energy output model the wind data was converted to 80m height, fitted to a Rayleigh distribution, fitted to a wind turbine power output curve typical of a 3 MW wind turbine, and then averaged over the baseline period.

Actual positions and sizes of all known operating and potential future (in-construction, consented & in planning) wind farm locations were projected onto the baseline wind energy output model, output for each of the locations were collected and accumulated to create a UK onshore wind energy model that closely reflected the actual present and future distribution of wind farms over the UK.

Output from the Met Office Hadley Centre RCM HadRM3 11-ensemble runs were used to generate wind climate change projections for the 2050s and 2080s periods. Output from the 11 runs for the future periods were fitted to a student t-distribution. Wind speeds for the 10%, 50%, and 90% points on the distribution of the 2050s and 2080s were compared with Had RM3 wind speeds for the baseline period and percentage of change from baseline values were generated. The percentage of change values were applied to the baseline wind speed model generated from the Met Office observed gridded wind speeds and future wind energy output over the UK were generated for the 2050s and 2080s (10%, 50%, 90%) distribution points. The projected wind energy values at each of the wind farm locations were again accumulated and the changes in wind energy from the baseline model were investigated.

4.2 Baseline Resource

The aim of the first part of the chapter was to create an accurate geographical map of both wind speed and wind energy resource over the UK to represent the present (baseline) climate. Wind speed in the UK is measured by an anemometer, and recorded at many weather station locations throughout the UK and Northern Ireland. The Met Office 5km observed gridded data sets (Met Office 2009b) include monthly average wind speeds and are used as the main date source to generate the wind speed and energy baseline models.

4.2.1 Creation of UK onshore baseline wind model

Wind speed data from Met Office 5km gridded wind speed data sets (Met Office 2009b) was used to develop the baseline wind speed model. The gridded wind speed data sets were subjected to regression and interpolation to generate regular values from the irregular station network, the dataset output also takes into account other attributes such as location, altitude, terrain, coastal influence, and land use (Perry *et al.* 2005a, 2005b). All individual cells of the 30 years of gridded wind speed data were checked for missing data. Linear interpolation from adjacent cells using a least square method was used to replace any missing values. All wind data was converted from the standard met station anemometer height of 10m to a height of 80m to represent the wind speed at a typical large scale wind turbine hub height as wind speeds increase the further they are from the ground as there is reduced friction between the atmosphere and the Earth's surface.

Wind speed can be estimated from a reference height to another height by use of the log power law (Manwell *et al.* 2002)

$$\frac{v(z)}{v(z_r)} = \ln\left(\frac{z}{z_o}\right) \Big/ \ln\left(\frac{z_r}{z_o}\right) \quad \textbf{(4-1)}$$

where $v(z)$ is the wind speed at height z , $v(z_r)$ is the wind speed at the reference height, and z_o is the surface roughness length (Manwell *et al.* 2002). A rough terrain such as a forest would have more of an effect on decreasing the wind speed than smooth terrain such as a calm sea. A surface roughness length relating to a 'fallow field' was assumed for the entire grid area. This is reasonable as the aim is to consider the impact of climate change on the UK as a whole rather than a specific site.

The 80m gridded wind speed data was then averaged over the baseline period. The resulting data was processed using Matlab and converted to 'ArcGIS' format to complete the UK onshore wind speed baseline model. Figure 4-2 shows the baseline onshore wind resource at a hub height of 80m for winter summer and annual periods. Spring and autumn are shown in Figure B-1 in Appendix B.

Onshore wind speeds are extremely geographically variable due to land terrain. This is especially true in mountainous regions such as in the Scottish highlands which have many of the windiest locations. Lowlands such as south-east England experience wind speeds that are both lower and much more uniform. There are higher wind speeds seen in many coastal and island locations. The west coast has higher wind speeds then the east due to prevailing Atlantic Ocean winds. Winter months have higher average wind speeds than other seasons, summer months are less windy.

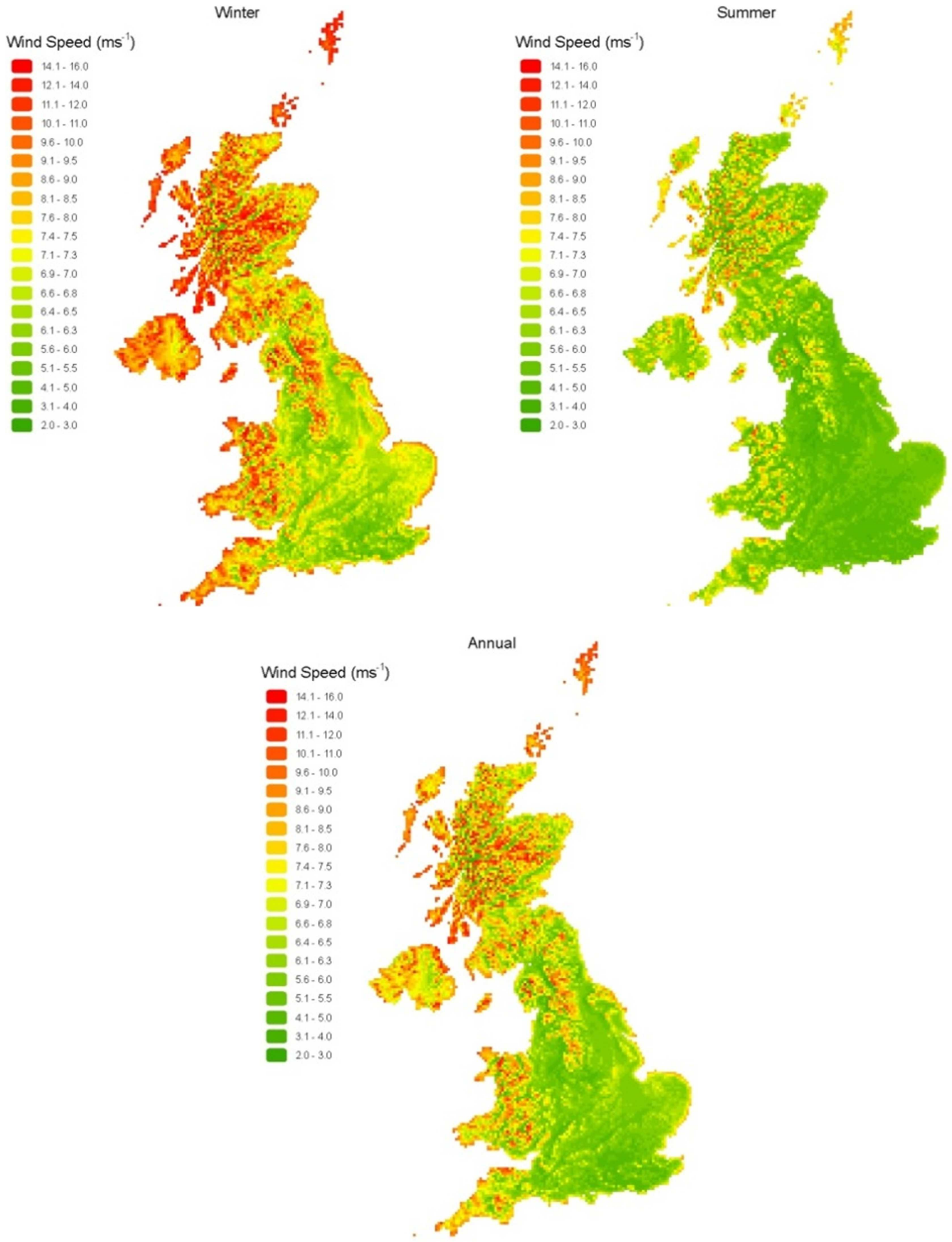


Figure 4-2: UK baseline onshore average wind speed resource at 80m height

4.2.2 Creation of UK onshore baseline wind energy model

The UK onshore wind energy baseline model was developed from the same source of gridded wind speed data as used in section 4.2.1. The wind speeds were converted to a hub height of 80m, as before. The power generated from a wind turbine cannot be accurately estimated using just the average monthly wind speed because of the cube relationship between wind speed and wind power, as shown in equation (4-2). The power P (W) available from wind is given by

$$P = \frac{1}{2}\rho A U^3 \tag{4-2}$$

where ρ is the air density (~1.2 kg/m^3), A is the swept area (m^2) and U is the wind speed (m/s).

4.2.2.1 Modelling the wind speed variability using a Rayleigh Distribution

The probability of occurrence of a given mean wind speed is generally characterised by either a Rayleigh or Weibull probability distribution curve (Manwell *et al.* 2002). The Weibull distribution has the advantage of being able to be tuned to a specific site using its two parameters controlling the ‘shape factor’ (*k*) and ‘scale factor’ (*c*). The Rayleigh distribution when used with a shape factor of 2 (*k* = 2) is a special case of a Weibull distribution and is typical of many locations and often applied over large areas. There have been many wind resource studies that have relied upon it (Breslow *et al.* 2002; Harrison *et al.* 2005; Harrison *et al.* 2008). The European Wind Energy Atlas (Troen *et al.* 1989) has extensive wind characteristic data, including shape factors, for locations throughout the UK. They vary quite considerably depending on the location and terrain but it is evident that the Rayleigh distribution is a good typical representation of a generic UK wind speed profile.

A Rayleigh distribution was used to model the variability of all the gridded wind speed data over the baseline period. The Rayleigh probability density function is given by

$$p(U) = \frac{\pi}{2}\left(\frac{U}{\bar{U}^2}\right)\exp\left[-\frac{\pi}{4}\left(\frac{U}{\bar{\bar{U}}}\right)^2\right] \tag{4-3}$$

and the cumulative distribution is given by

$$F(U) = 1 - \exp\left[-\frac{\pi}{4}\left(\frac{U}{\bar{\bar{U}}}\right)^2\right] \tag{4-4}$$

where $\overline{U}$ is the average wind speed (m/s).

A Monte Carlo approach was used to generate a Rayleigh distribution from each monthly mean wind speed over the thirty year period for each of the model grid cells. An output sample size of 100,000 datapoints, the sample size being set as high as possible without the Matlab program taking too long to process all the data. The wind speed distribution output for each cell was applied to a generic power curve based on the Vestas V90 3.0 MW power curve (Figure 4-3). The average monthly energy output was then calculated.

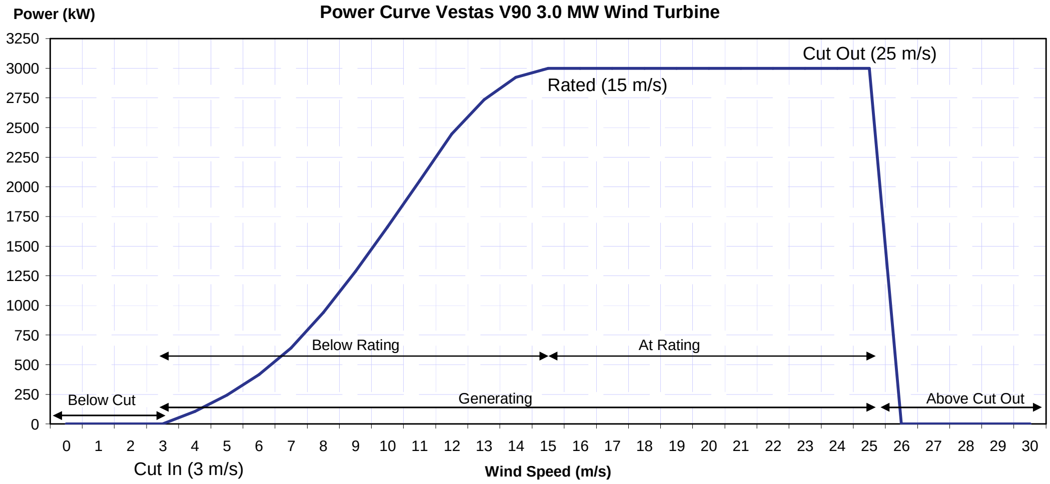


Figure 4-3: Vestas V90 3MW Power Curve (Vestas 2011)

At this stage all grid cells for each month of each year are estimations of possible energy output for a generic 3 MW wind turbine. The parameter outputs are finally averaged together over the 30 year baseline period to create the average gridded onshore baseline wind energy model. The described method is similar to the approaches by Boehme *et al.* (2007) and Harrison *et al.* (2008).

Figure 4-4 shows the winter, summer and annual UK baseline capacity factors for winter months. Spring and autumn are shown in Figure B-2 in Appendix B. The geographical and intra-annual variability of capacity factor closely follows that of wind speed, however, there is what could be described as a smoothing effect in locations with rough terrains with high wind speeds where the wind speeds occurring above the cut-out speed limits the capacity factor values. The values can vary significantly from winter values approaching 60% in unsheltered rough terrain locations, down to approaching 6% in summer months in more sheltered rough terrain locations. The south-east England which is largely flat lowland, can see typical values of around 16% in summer months and 27% in winter. Obviously, onshore wind farms are generally situated at locations with favourable wind speeds. Different specification of wind turbines would be chosen to suit the wind resource at the specific location.

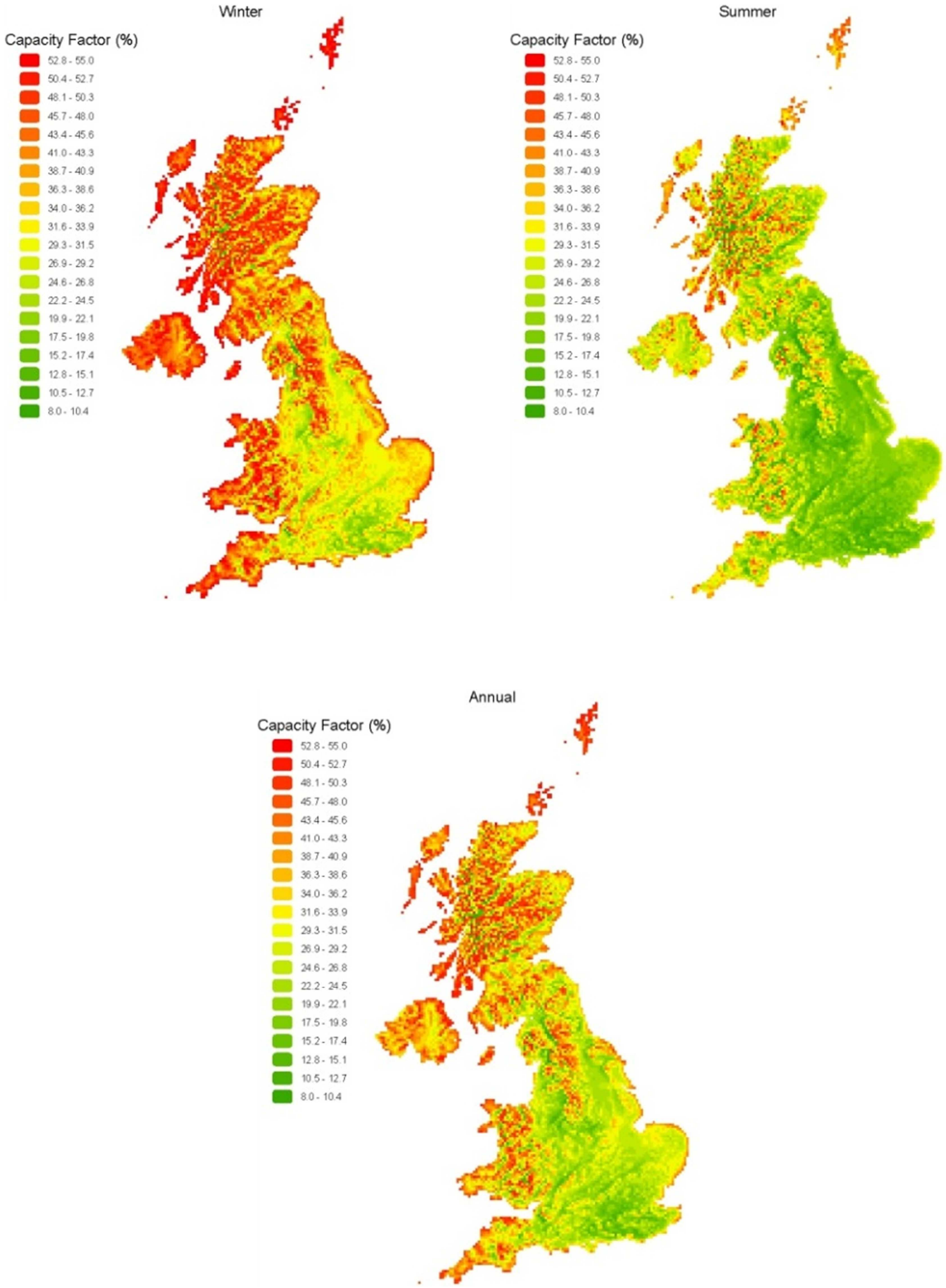


Figure 4-4: Seasonal onshore baseline capacity factors

4.2.2.2 Other modelled wind turbine parameters

Shown on the wind turbine power curve (Figure 4-3) are some other wind turbine parameters: ‘Cut In’ is the wind speed at which the wind turbine starts to generate. ‘Cut Out’ is the wind speed at which the wind turbine shuts down to avoid damage from excessive wind conditions. ‘Rating’ is the minimum wind speed at which the wind turbine generates its maximum rated value.

There are other useful wind turbine baseline parameters that have been extracted while performing the analysis to generate the UK onshore wind energy baseline model and these parameters are shown in Table 4-1 and also in Figure 4-3.

Vestas V90 3.0 MW Wind Turbine Parameters and Terms	
Cut In	3 m/s
Rated	15 m/s
Cut Out	25 m/s
Below Cut In	< 3m/s
Below Rating	3 - 14.9 m/s
At Rating	15 - 25 m/s
Generating	3 - 25m/s
Above Cut Out	> 25 m/s

Table 4-1: Wind Turbine parameters and wind speed values for Vestas V90 3.0 MW Turbine

Knowing the proportion of time a wind turbine spends in different states can give very useful information to wind farm and turbine developers. The UK onshore wind energy baseline model includes the average proportion of time spent in different states. The values, like the capacity factor, are dependent on the characteristics of the turbine as well as the wind characteristics and there are many different operational wind turbines with varying characteristics. It is assumed here that the Vestas 3MW turbine gives relatively typical characteristics for a large wind turbine.

To better understand the different wind speeds and wind turbine availability parameters and how their values vary depending on a particular locations wind characteristics 11 different UK locations are shown in Figure 4-5 and annual parameters for the locations shown in Table 4-2. It is clear that more northerly and westerly locations are exposed to a larger wind resource and higher capacity factors and will spend more time at full rating. However, they are also more likely to experience times of shut down due to excessive wind speeds. More southerly and eastern locations generally have less wind resource and lower capacity factors with less time at full rating and a larger proportion of time with no generation due to low wind speeds. See Appendix B-3 to B-8 for wind turbine parameter states and figures showing proportional time in these states over the UK.

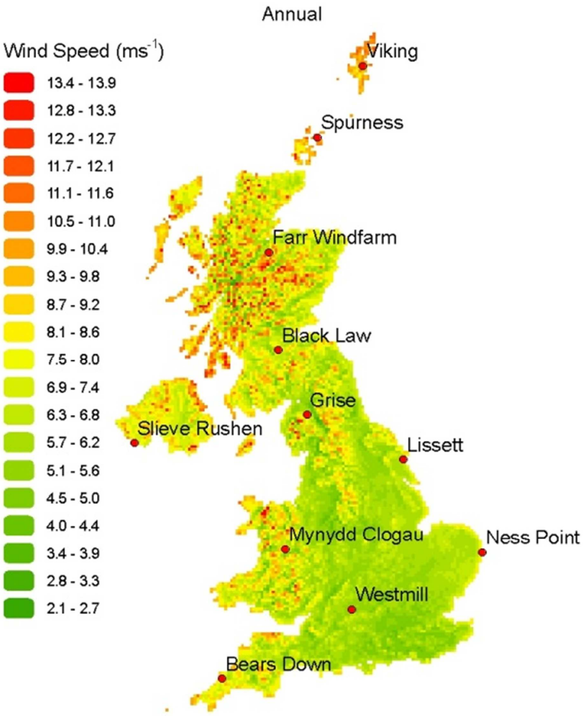


Figure 4-5: Different Wind Farm Site Locations

Location	Average Wind Speed	C. F.	> Cut Out	Rating	Generating	< Rating	< Cut In
	(m/s)	*%*	*Time (%)*				
Viking	9.4	48.0	4.7	22.6	85.3	62.7	10.0
Spurness	10.0	50.5	6.2	25.5	85.1	59.6	8.7
Farr	8.9	44.4	4.3	19.6	84.1	64.5	11.7
Black Law	7.1	35.5	1.1	11.6	82.1	70.5	16.8
Grise	7.0	34.7	1.1	10.9	81.9	71.0	17.1
Slieve	12.2	51.4	14.0	29.7	79.6	49.9	6.5
Lissett	6.3	29.6	0.4	7.3	79.8	72.5	19.8
Mynydd	9.5	48.1	5.1	22.8	85.1	62.3	9.9
Ness Point	7.4	37.7	1.0	12.4	83.9	71.5	15.2
Westmill	5.5	22.2	0.1	3.6	74.7	71.1	25.2
Bears Down	8.9	46.7	3.3	20.6	86.0	65.4	10.7

Table 4-2: Wind turbine parameters values at eleven locations with different wind characteristics

4.2.2.3 Uncertainties

The data and method contain a number of uncertainties. The accuracy of the met stations readings are generally within a few percent, but poorly maintained sites and irregularities in the surrounding location such as buildings and trees can introduce larger errors. The grid resolution does not capture all characteristics of the terrain and will lead to less wind flow detail. The roughness length relating to a ‘fallow field’ was used over all locations and this will add an error in locations, especially in wooded and built up areas. A standard Rayleigh wind distribution was assumed for all locations, this is an acceptable method when working with such a large area; however it may add large uncertainties in locations with different wind distributions. There has been a generic power curve assumed for the power conversion which will add additional error. The wind to power conversion process does not capture any turbulence issues.

4.3 Data Analysis and Validation

The aim of this section is to compare the onshore baseline wind speed model and wind energy model with other available sources including historical observation values.

4.3.1 Wind Resource

Wind speed values from the baseline wind speed model at onshore wind farm locations were compared with two other sources of long term average wind speeds and results are shown in Figure 4-6.

The two other wind speed database sources are:

- The DECC wind speed database (DECC), previously known as the NOABL (Numerical Objective Analysis of Boundary Layer) wind speed database. The wind speed data was converted from a reference height of 10m to 80 m. The resolution was also changed from 1km to 5km to match the baseline model.
- Edinburgh Wind Model (EWM) (Hawkins 2012) 3km resolution at 80m height.

As can be seen from Figure 4-6 there is good agreement between the baseline, DECC and EWM annual wind speed values. The aggregate average annual wind speeds and RMSE values are shown in Table 4-3. The baseline model wind speeds appear to be an average of approximately 0.5 m/s higher than the two other sources across the UK. The agreement is reasonable given the different time periods over which the three models are operating (Table 4-3).

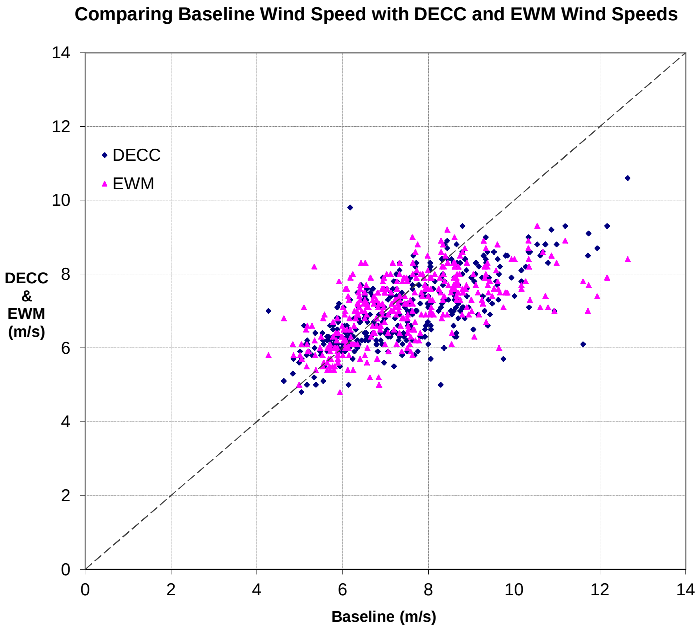


Figure 4-6: Scatter plot comparing baseline annual wind speeds at onshore wind farm locations with DECC and EWM (Hawkins 2012) wind speeds

Source	Time Period	Aggregate Wind Speed	RMSE from Baseline
Baseline	1961-1990	7.58	-
DECC	Mid 1970s – mid 1980s	7.06	1.29
EWM	2000 – 2010	7.14	1.19

Table 4-3: Comparison of Aggregate average annual wind speeds and RMSE values from the baseline wind speeds

4.3.2 Observations at Operational Onshore Wind Farms

There is limited publicly available historical data on statistical performance of onshore wind farms. The Renewable Energy Foundation database of renewables obligation generators (REF 2011) contains reported monthly average capacity factor values of operational wind farms but does not include other parameters such as observed wind speeds and technical availability of the wind turbines.

Figure 4-7 shows a scatter plot comparing the modelled annual baseline capacity factors and the rolling annual averages of actual capacity factors (REF 2011) from 75 operating onshore wind farms. The wind farms used met a criteria of having an accreditation date of before 2007 and also a wind farm installation size in excess of 3 MW.

The aggregate modelled capacity factor is 40% and the aggregate observed rolling capacity factor is 26.7%. This implies that the modelled capacity factors are an average of 13.3% higher than actual observed values and have a RMSE of 15.4%.

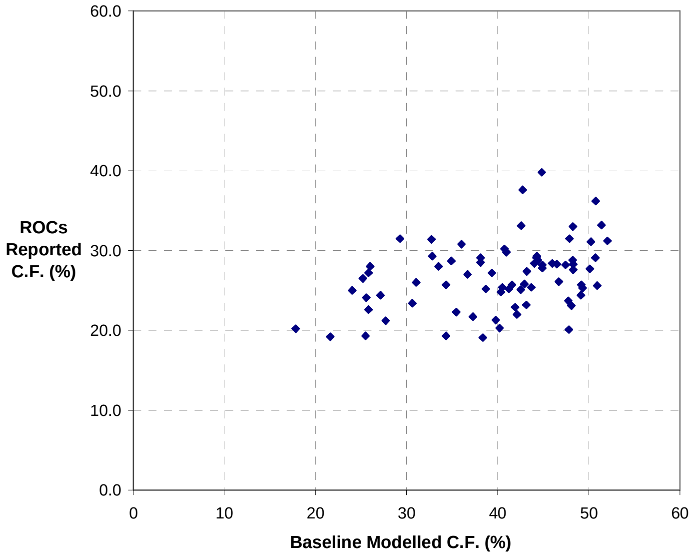


Figure 4-7: Scatter plot of Baseline Modelled and ROC reported capacity factors

There are several potential reasons why the modelled baseline wind speed characteristics are higher and vary from the observed values:

- The modelled data is averaged over a 30 year period and captures a wider spectrum of the natural variability of the wind climate, but the observed values are averaged over a shorter period as they are restricted by the accreditation date of the wind farm (averaged over a period of 3 to 7 years depending on accreditation date).

- The modelled data used a standard Rayleigh distribution for all locations, but each wind farm location would have its own very specific wind distribution and turbulence characteristics, largely dependent on the location and surrounding terrain.

- The modelled data does not account for closely situated obstacles such as houses and trees that would change the wind characteristics.

- The modelled data does not account for ‘array wake loss’ which is made up of several functions including downwind and crosswind spacing, and turbulence intensity within a wind farm array. The lower capacity factor displacement of the real data is very likely to be at least partially due to the ‘array wake loss’ experienced within a wind farm array.

- The modelled data assumes 100% technical availability of all wind turbines. The observed data will include shut down periods for planned and unplanned maintenance.

- The modelled wind speed data is referenced to a hub height of 80m, whereas the actual hub height of onshore wind farms vary quite considerably and the majority being much less than 80m.

- The modelled data assumes new efficient wind turbine technology, whereas many operating wind turbines use older, less efficient technology.

4.3.3 Wind Energy Losses

Technical availability is the percentage of time the wind farm is available for generating electricity. Renewable UK state that technical availability of modern turbines is typically 98% or better (Renewable UK 2011c), For this study, an overall technical availability value of 96% will be assumed, the slightly lower figure is intended to account for older operational turbines. An array wake loss value of 10% will be assumed. Many Onshore wind farms are situated in very remote locations where there is often a weak distribution grid connection to the transmission grid network. A 3% electrical loss will be assumed.

4.3.4 Capacity Factor Comparison with Assumed Wind Energy Losses

Figure 4-8 shows the same scatter plot as shown earlier in Figure 4-7 which compares observed average capacity factors of 75 wind farms with modelled data from the same location. However, now the modelled data has the assumed wind energy losses discussed in 4.3.3 incorporated in the modelled annual baseline capacity factors. The aggregate modelled capacity factor with assumed losses is now 33.5% and now gives a difference of 9.5% between the modelled and observed values and a much improved RMSE value of 6.8%.

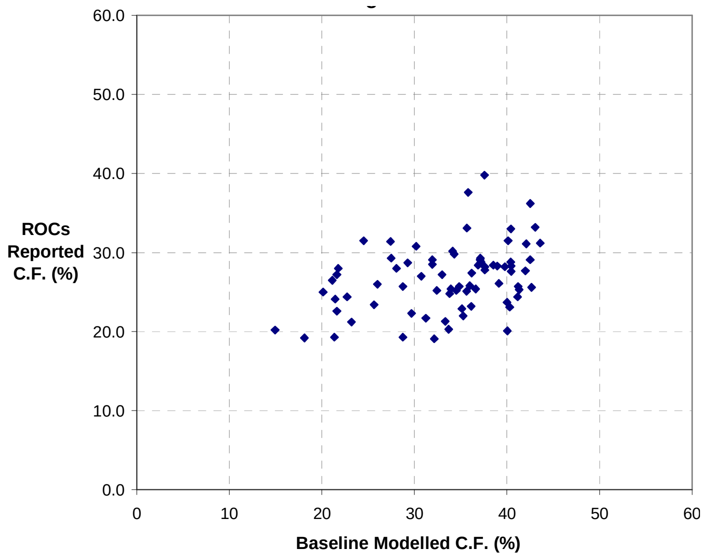


Figure 4-8: Scatter plot of Baseline Modelled and ROC reported capacity factors including assumed losses

4.4 UK Potential Onshore Wind Energy Resource

Onshore wind power is now an established and mature renewable technology. In the UK there are presently over 270 operational onshore wind farms with the total installed capacity exceeding 3.8 GW and these numbers are set to grow substantially: there are a further 34 wind farms (1.4 GW) in construction, 196 wind farms (3.6 GW) consented, and a further 256 wind farm projects (6.8 GW) in planning (Renewable UK 2011).

4.4.1 Deployment method

For this study, the method used to evaluate the present UK baseline onshore wind resource characteristics was to identify as many of the onshore wind farm locations that are known operational, in construction, consented and in planning and to model them using data from the UK onshore baseline wind energy model (section 4.2.2), the size of the wind farm and the assumed losses (section 4.3.3). A total of 472 locations with a total installed capacity of 12.48 GW were included in the analysis. The locations are shown in Figure 4-9.

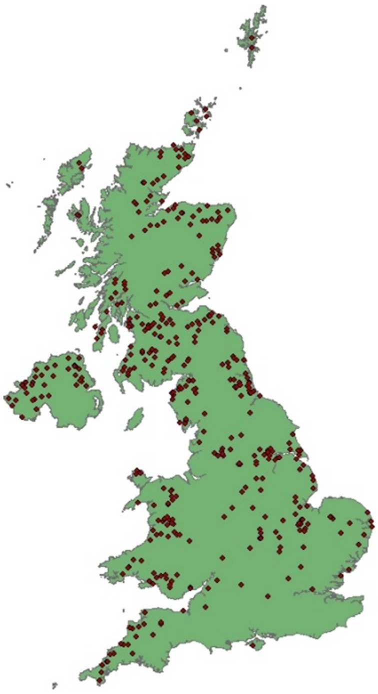


Figure 4-9: Wind farm locations used for analysis of the baseline UK onshore wind energy resource characteristics

To calculate the overall UK onshore baseline capacity factor values, as shown in Table 4-4 the monthly capacity factors for each location were weighted by the location's installed capacity value and all locations aggregated together. The overall installed capacity comes to a total of 12.44 GW. The total baseline annual energy output without loss assumptions is 45.85 TWh with an average annual capacity factor of 41.9%. Monthly, annual, no losses and with losses figures are shown in Table 4-4.

	Overall Baseline Capacity Factors (%) and Energy Output (TWh)												
	ANN	**JAN**	**FEB**	**MAR**	**APR**	**MAY**	**JUN**	**JUL**	**AUG**	**SEP**	**OCT**	**NOV**	**DEC**
	No Losses												
C.F. (%)	41.9	49.8	48.3	48.7	42	37.9	36.4	31.6	30.9	40.8	43.3	46.4	47.9
Energy (TWh)	45.85	4.62	4.05	4.52	3.77	3.52	3.27	2.93	2.87	3.66	4.02	4.16	4.45
	With Losses												
C.F. (%)	35.1	41.7	40.4	40.8	35.2	31.8	30.5	26.4	25.9	34.1	36.3	38.8	40.1
Energy (TWh)	38.42	3.87	3.39	3.79	3.16	2.95	2.74	2.46	2.41	3.07	3.37	3.49	3.72

Table 4-4: Baseline Capacity Factors - Aggregate Total

Figure 4-10 shows the UK overall baseline capacity factors and energy output including the loss assumptions (discussed in section 4.3.3). The total baseline annual energy output including losses is 38.4 TWh, with an average annual capacity factor of 35.1%.

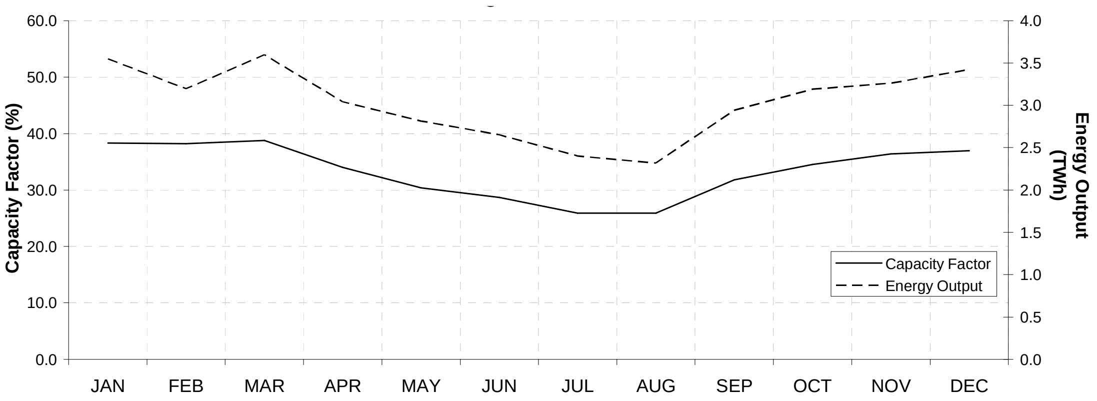


Figure 4-10: Monthly onshore capacity factors and energy output – Aggregate total including assumed losses

The UK annual baseline capacity factor has been estimated at 35.1% (Table 4-4). This does include assumed losses but is 8% higher than estimations of UK onshore wind historical average capacity factors values (DUKES 2010) as shown in Table 4-5. This figure is in line with the 9% difference in capacity factor discussed earlier in section 4.3.4. This difference is assumed to be largely due to two factors:

UK Average Onshore Wind Historical Capacity Factors					
2005	2006	2007	2008	2009	Average
26.4	27.2	27.5	27.0	27.4	27.1

Table 4-5: Historical Average UK Onshore Wind Capacity Factors (DUKES 2010)

Firstly, many of the existing onshore wind turbines are at lower hub height than 80m and are potentially performing less efficiently than modelled due to the lower height and resulting lower wind resource. Secondly, the power curve used is for a Vestas V90 turbine and most probably attributable to ideal wind conditions. Many of the onshore wind turbines are not 3MW Vestas wind turbines and in many cases have lower performance curves – partly due to having different wind-power characteristics and partly from the location having less than ideal wind conditions.

There is an option of either adding another “loss” into the wind energy losses discussed in section 4.3.3 to compensate for the difference between the modelled and observed overall capacity factor for onshore wind in the UK. However, for the purpose of this study, the modelled data will be kept as it is. Many of the onshore wind sites used here are planned sites not yet operational and many of these, when operational, will benefit from larger turbines with higher hub heights that are situated at more optimal geographic locations. These factors all lead to better overall performance of onshore wind than the historic record indicates.

4.5 Climate Change Impact

The aim of this section is to investigate the impact of climate change on the baseline energy output of potential deployments of onshore wind energy. It does not capture diurnal changes or increases in storminess. The method described is specifically investigating the climate change impact on long term averages of intra-annual and annual average variability. As previously mentioned, probabilistic projections of surface wind speeds were not initially included in the UKCP09 report due to too much wind speed uncertainty between the different climate models used in the report. However, daily wind speed projection data is available from the Met Office, HadRM3 model 11-ensemble runs. This is the key regional climate model used to generate the UKCP09 future climate projections.

4.5.1 HadRM3 Wind Speed Projections

The following describes how wind speed data from the HadRM3 model were processed into a format similar to that of the UKCP09 probabilistic projections:

The HadRM3 data is available from the BADC in NetCDF form and not via a user friendly interface like the UKCP09 official data. There are no probabilistic distributions and only the medium emissions scenario output data is available.

The 11-ensemble runs were downloaded for the years 1961-2099. For each of these:

1. The daily average wind speed data was extracted for three 30 year periods: the baseline (1961-1990), the 2050s (2040-2069) and the 2080s (2070-2099)
2. The monthly average wind speeds were averaged over each of the 30 year time periods.
3. The monthly averages for each time period were averaged over the 11 ensemble runs.

Figure 4-11 shows the UK annual average monthly wind speeds for the baseline, 2050s and 2080s time periods at a height of 10m. They are shown on the HadRM3 rotated grid with 25km resolution grid cells. Offshore grid cells are shown, but are only used in the following chapter on offshore wind.

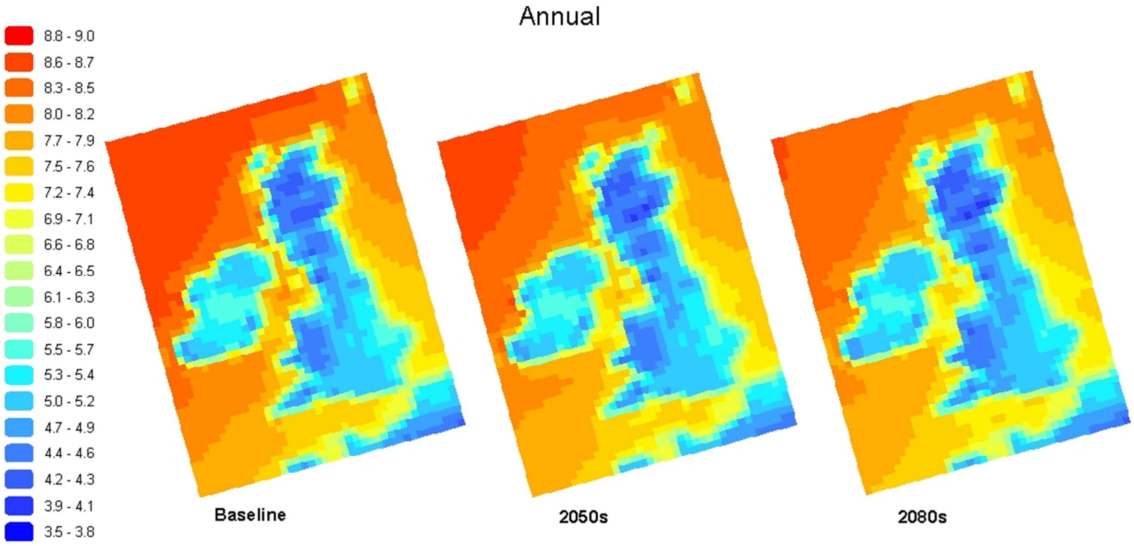


Figure 4-11: Averaged annual 10m height onshore wind speeds in the baseline, 2050s and 2080s periods - calculated from HadRM3 11-ensemble.

4.5.2 Probabilistic wind speed projections from the HadRM3 model data

The outcome of this section does not replicate the process UKCP09 used to generate its probabilistic projections for other variables. The intention is to estimate the distribution of the average monthly wind speeds over the 11 runs of the HadRM3 output and to generate average monthly wind speed output data for the 2050s and 2080s at 10%, 50% and 90% confidence points (probability levels) of the probability distribution by using the student t-distribution method.

4.5.2.1 The student t-distribution

The student t-distribution is often used when there is a small sample size, the distribution is symmetrical and the variance of the underlying population is unknown. Both are true in the case of the HadRM3 11-ensemble runs. The student t-distribution population return for a specific confidence level can be calculated by

$$\overline{X} \pm t_{\alpha} SE_{\bar{x}} \qquad \textbf{(4-5)}$$

where $\overline{X}$ is the sample mean, t_{α} is the t-value of the student t-distribution $SE_{\bar{x}}$ is the standard error of the mean, which can be calculated by

$$SE_{\bar{x}} = \frac{s}{\sqrt{n}} \tag{4-6}$$

where s is the sample standard deviation and n is the number of samples. The t-value t_{α} is a function of the probability and the degrees of freedom, where the probability is (1−confidence level) and degrees of freedom = (n−1).

An example student t-distribution is shown in Figure 4-12. The shape is dependent on the degrees of freedom. A higher degree of freedom results in the student t-distribution more closely fitting to a normal distribution. Fewer degrees of freedom result in heavier tails with more samples falling further from the mean.

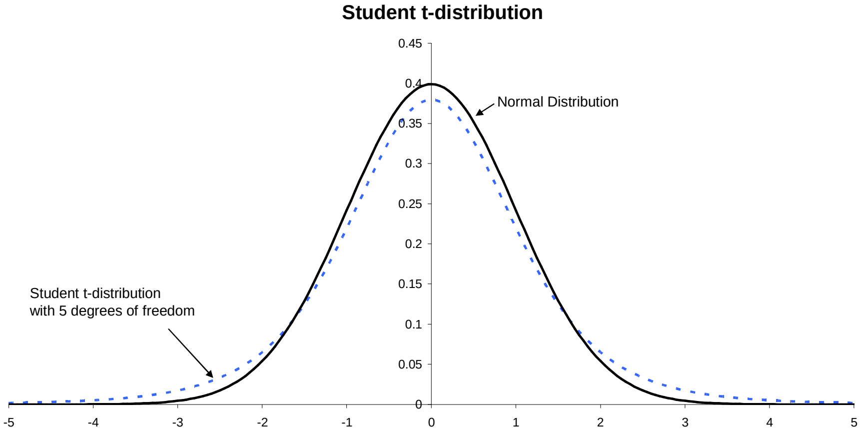
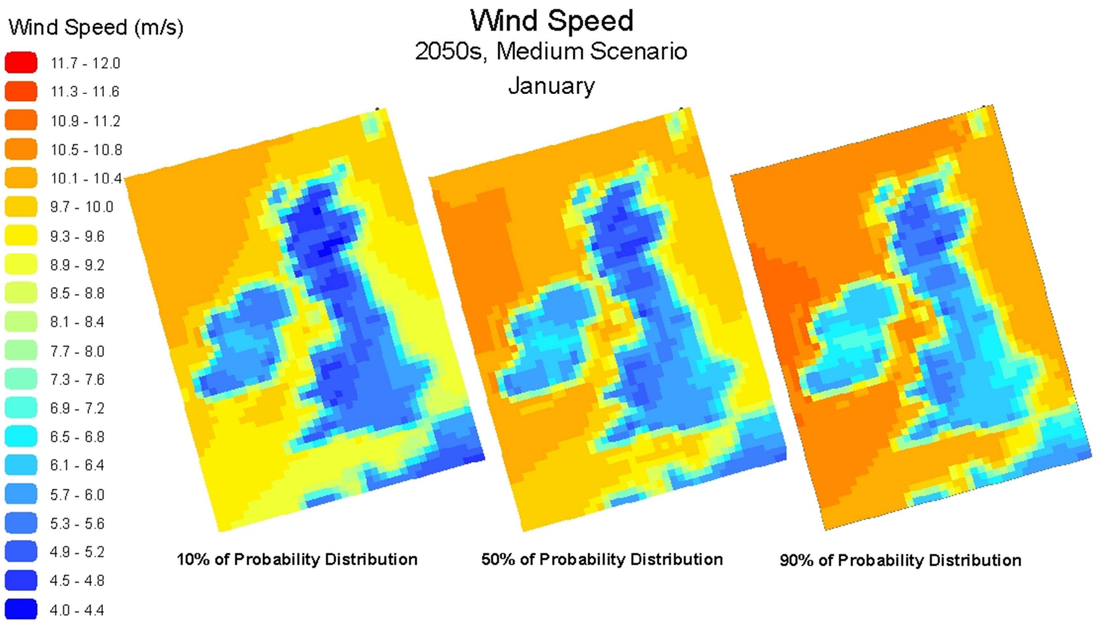


Figure 4-12: Example of a student t-distribution.

4.5.2.2 Applying the student t-distribution to the HadRM3 Projected Wind Speed Data

The student t-distribution method was used to estimate 10% and 90% confidence intervals of the average wind speed distribution over the 11 ensemble runs for the 2050s and the 2080s time periods. The 50% confidence level is equal to the sample mean. Figure 4-13 shows the 50%, 10% and 90% probability level 80m height HadRM3 wind speed output for the month of January in the 2050s period for a medium emissions scenario.



10% of Probability Distribution

50% of Probability Distribution

90% of Probability Distribution

Figure 4-13: Projected average January wind speeds for 2050s medium scenario

4.5.3 UK Onshore Wind Speed Projections

The UK onshore baseline wind model (described in 4.2) is more realistic than the onshore baseline wind speeds generated from the HadRM3 model. It has better resolution and has been derived from actual observed data whereas the HadRM3 is dynamically downscaling output from a GCM. The HadRM3 wind speed data also has biases over land resulting in lower than expected wind speeds over mountainous locations and slightly higher than expected wind speeds over low land locations (Brown *et al.* 2009).

For the above reasons the HadRM3 has not been used to directly estimate actual onshore wind speed values for the baseline period (or the 2050s or 2080s). Instead, it has been used to calculate the relative percentage change between its baseline and the 2050s and 2080s 10%, 50%, and 90% confidence intervals for all months.

The wind speed percentage change values for both future time periods and confidence levels were used to adjust the baseline wind speed and wind energy statistics. The processes described in sections 4.2.1 and 4.2.2 were repeated using the projected percentage change wind speed data to generate average monthly wind speed and wind energy data for the future periods.

Figure 4-14 shows annual projections for the 2050s and 2080s. Most locations show very slight negative changes with these negative changes being stronger in many coastal locations. There are some locations in the Scottish Highlands showing slight positive changes. The 2080s show stronger negative changes throughout the UK.

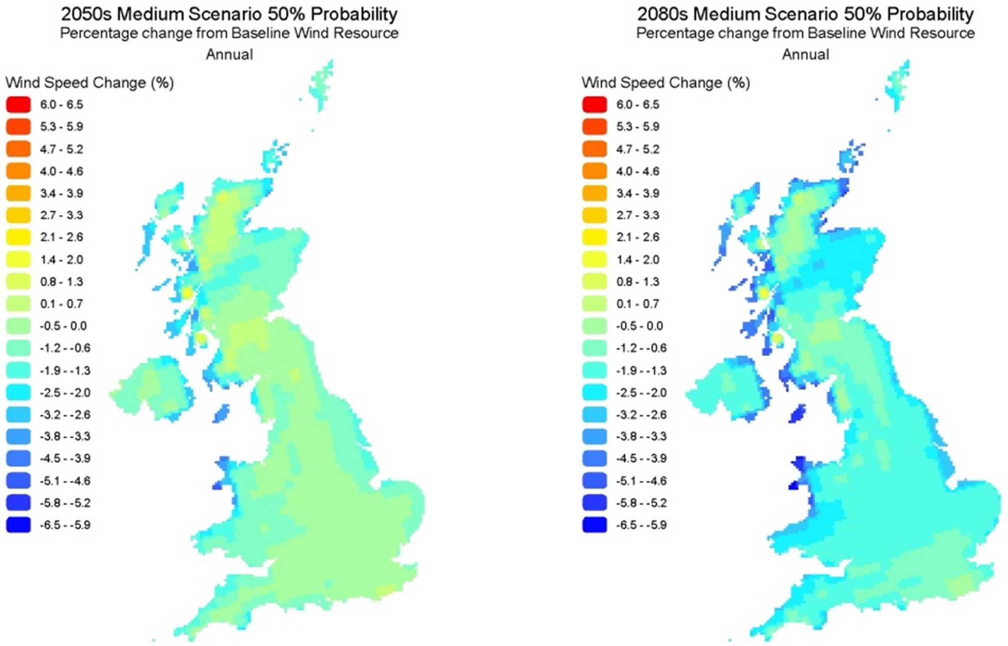


Figure 4-14: Annual projections for 2050s (left) and 2080s (right) for a medium emissions scenario with 50% probability level.

Summer projections are shown in Figure 4-15 and follow a similar pattern to the annual projections. The 2050s have generally negative changes which are stronger in locations closer to the coast; there are some positive changes in the Scottish Highlands. The 2080s show similar patterns to the 2050s but with all locations being skewed towards more negative changes.

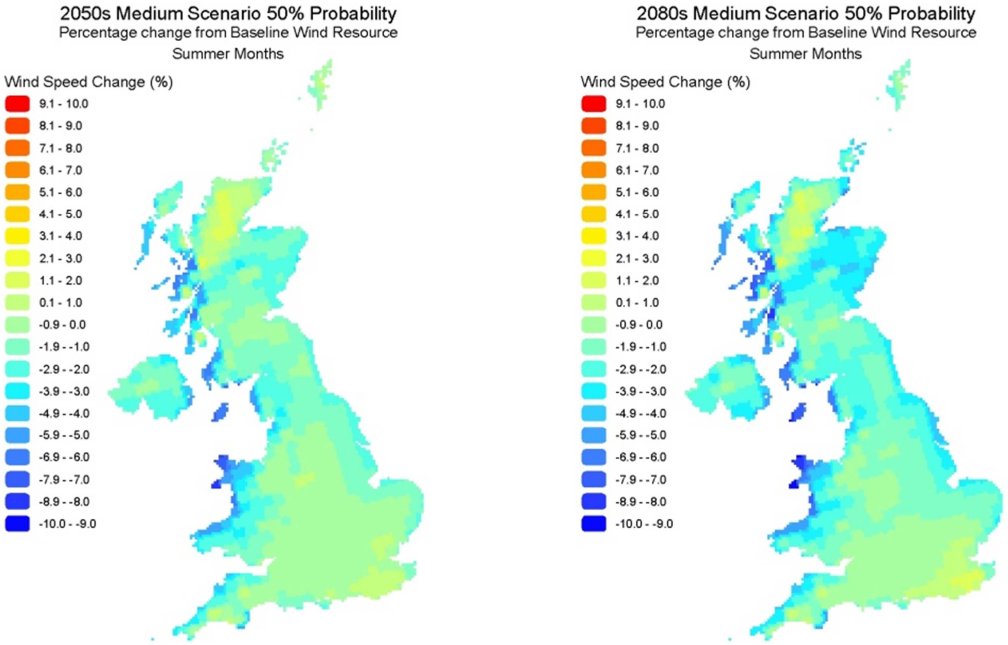


Figure 4-15: Summer projections for 2050s (left) and 2080s (right) for a medium emissions scenario with 50% probability level.

In winter months (Figure 4-16) there are both positive and negative changes with the negative changes generally in the north and changing more positive further south. The 2080s show all locations skewed towards more negative changes.

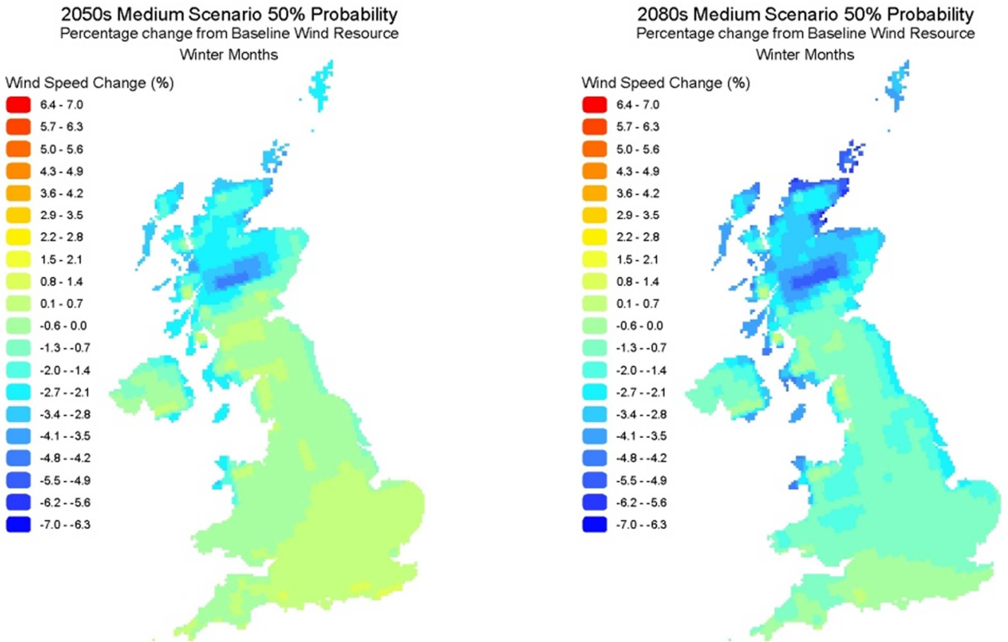


Figure 4-16: Winter projections for 2050s and 2080s for a medium emissions scenario with 50% probability level.

Figure 4-17 shows the UK onshore annual wind speed percentage changes from the observed baseline for the 2050s medium scenario at 10, 50 and 90% probability levels.

Table 4-6 shows the annual wind speed change for selected UK locations from the baseline to the 2050s and 2080s. It can be seen that all except one location (Black Law) show negative changes for the 2050s with the changes almost doubling by the 2080s. Black Law which shows a positive change in the 2050s turns negative by the 2080s. Uncertainties vary by location but are generally in the region of ±4.0% to ±6.0% for the 2050s and ±4.5% to ±7.0% for the 2080s.

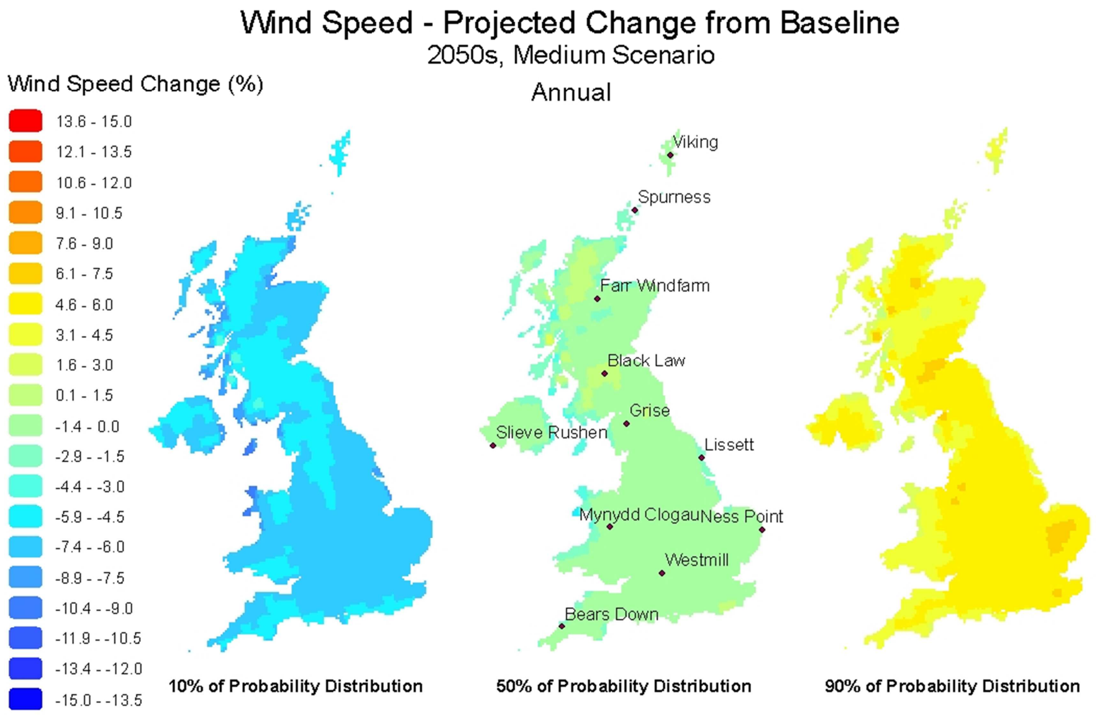


Figure 4-17: Projected annual wind speed percentage change for the 2050s medium scenario

Location	2050s			2080s		
	Probability Level (%)			Probability Level (%)		
	10	**50**	90	10	**50**	90
Viking	-4.9	**-0.7**	3.6	-5.4	**-1.0**	3.5
Spurness	-7.3	**-2.7**	1.8	-9.5	**-4.5**	0.6
Farr Wind farm	-6.6	**-0.7**	5.1	-7.5	**-1.6**	4.3
Black Law	-5.7	**0.2**	6.1	-6.2	**-0.6**	5.1
Grise	-5.9	**-0.7**	4.5	-6.8	**-1.6**	3.6
Slieve Rushen	-5.9	**-0.7**	4.5	-7.0	**-1.6**	3.7
Lissett	-7.4	**-1.7**	4.1	-9.0	**-3.0**	2.9
Mynydd Clogau	-6.4	**-0.9**	4.6	-8.0	**-2.0**	4.0
Ness Point	-6.8	**-0.9**	5.0	-8.2	**-1.9**	4.4
Westmill	-6.5	**-0.5**	5.5	-8.2	**-1.3**	5.5
Bears Down	-6.9	**-1.3**	4.3	-8.5	**-2.2**	4.0

Table 4-6: Projected annual wind speed change for selected onshore wind farm locations

4.5.4 UK Onshore Wind Energy Projections

Wind energy projections have been created for the projected 10%, 50% and 90% probability future wind speed projections. Figure 4-18, Figure 4-19 and Figure 4-20 show 2050s and 2080s projected capacity factor changes for a medium scenario at 50% probability for annual, winter and summer periods. The trends are very similar as the changes seen for wind speed, some locations with high wind resource appear more flattened and this it probably due to the wind turbine power curve causing a compressing effect on higher wind speeds due to the maximum capacity and cut-out.

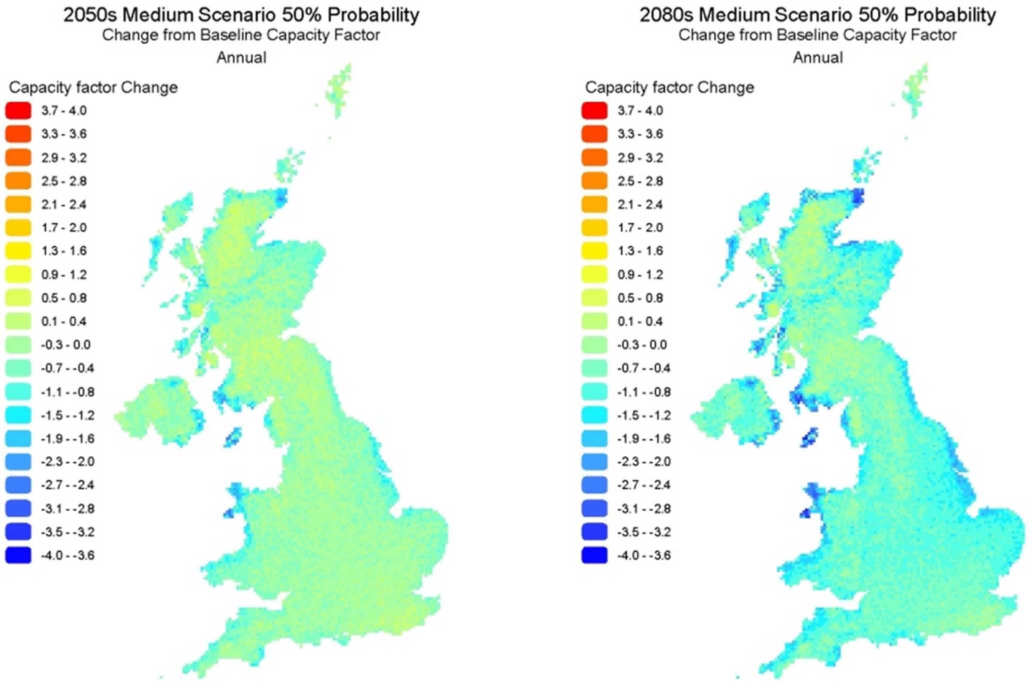


Figure 4-18: Projected annual capacity factor change for the 2050s and 2080s. 50% probability - medium scenario

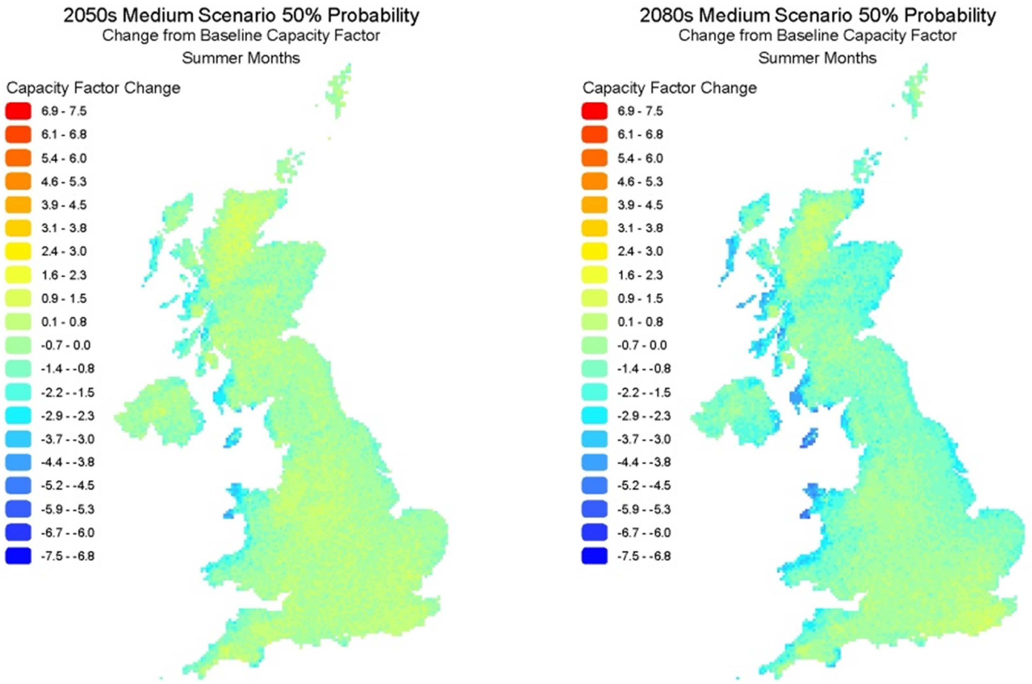


Figure 4-19: Projected Summer months capacity factor change for the 2050s and 2080s. 50% probability - medium scenario

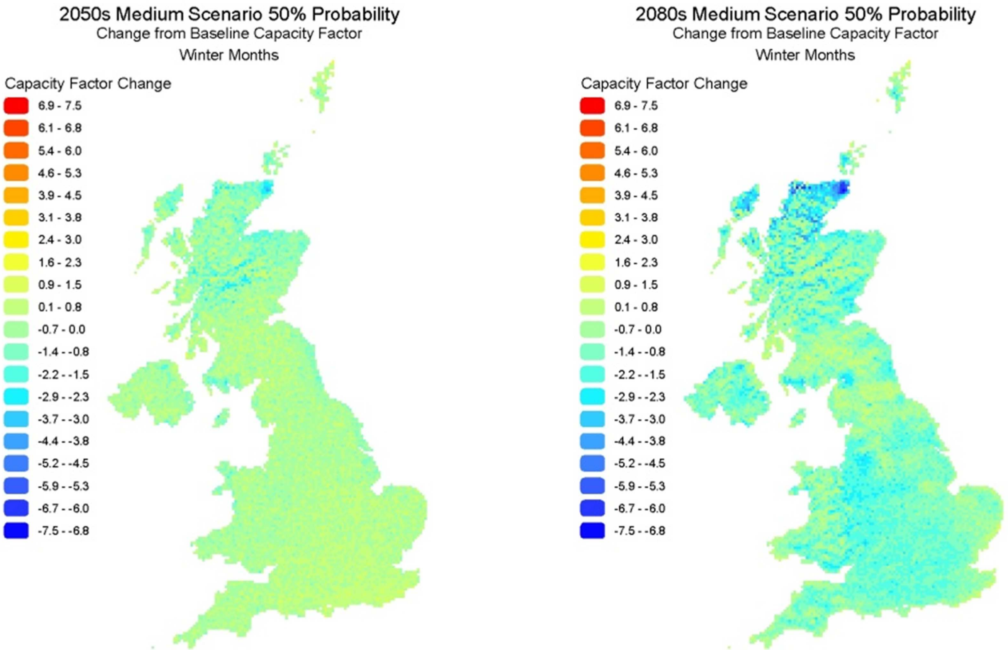


Figure 4-20: Projected Winter months capacity factor change for the 2050s and 2080s. 50% probability - medium scenario

The projected range of changes in wind energy capacity factor is shown for the 2050s and 2080s in Figure 4-21 and Figure 4-22.

This is the actual percentage point change in capacity factor and not the percentage change in capacity factor. The levels are typically -0.5% ±2% and -0.8% ±2% for the 2050s and 2080s medium emissions scenarios respectively.

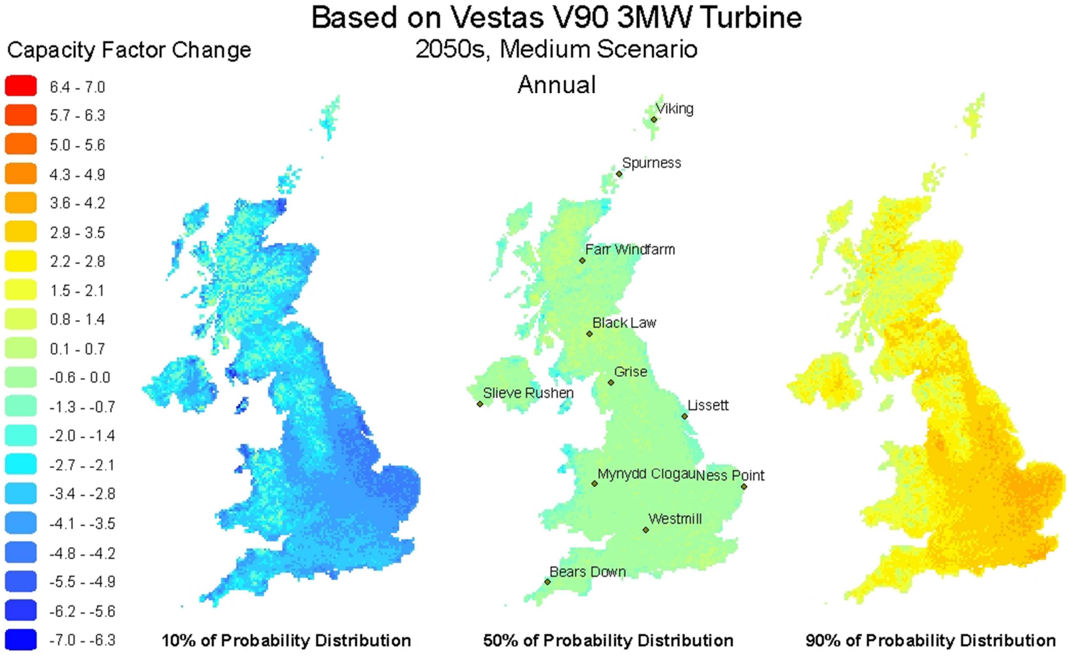


Figure 4-21: Projected annual capacity factor change for the 2050s medium scenario

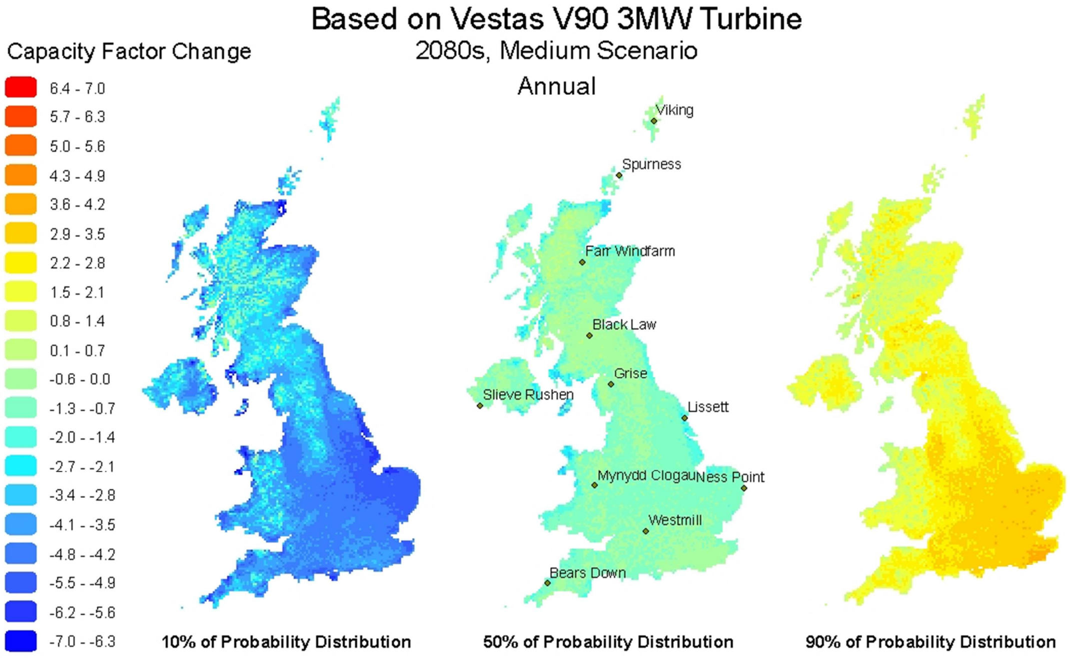


Figure 4-22: Projected annual capacity factor change for the 2080s medium scenario

Table 4-7 shows the relative capacity factor change for the selected UK locations in the 2050s and 2080s.

Location	2050s			2080s		
	Probability Level (%)			Probability Level (%)		
	10	**50**	90	10	**50**	90
Viking	-1.50	**0.03**	1.47	-1.80	**-0.05**	1.37
Spurness	-2.49	**-0.73**	0.64	-3.61	**-1.45**	0.61
Farr Wind farm	-1.94	**-0.34**	1.13	-2.14	**-0.64**	1.06
Black Law	-2.68	**-0.22**	2.46	-2.97	**-0.38**	2.24
Grise	-2.45	**-0.27**	2.02	-3.04	**-0.67**	1.75
Slieve Rushen	-0.50	**-0.17**	-0.32	-0.47	**-0.32**	-0.36
Lissett	-5.06	**-1.33**	2.49	-5.89	**-2.07**	1.60
Mynydd Clogau	-1.71	**-0.45**	0.73	-1.99	**-0.66**	0.60
Ness Point	-4.11	**-0.98**	2.56	-4.96	**-1.37**	2.28
Westmill	-3.38	**-0.03**	3.19	-4.37	**-0.73**	3.24
Bears Down	-2.99	**-0.81**	1.20	-3.36	**-0.87**	1.23

Table 4-7: Projected annual capacity factor percentage point change for selected onshore wind farm locations

To be able to better compare wind speed and capacity factor uncertainty Table 4-8 shows the percentage change of capacity factor for the selected UK locations in the 2050s and 2080s. It can be seen that percentage change uncertainties for capacity factor have a much larger spread than for wind speed. The 2050s see uncertainty spreads of up to −17.2% and +14.4%

and for the 2080s −19.9% and +14.6%. Coastal locations and the south east of England appear to have the largest capacity factor reductions.

Locations that have lower annual average wind speeds have the higher uncertainty of capacity factor and this is due to those locations having a higher proportion of time when the turbine is generating below the rated value. The capacity factor is therefore more sensitive to wind speed change.

Location	2050s			2080s		
	Probability Level (%)			Probability Level (%)		
	10	**50**	90	10	**50**	90
Viking	-3.13	**0.06**	3.06	-3.75	**-0.1**	2.85
Spurness	-4.93	**-1.45**	1.27	-7.15	**-2.87**	1.21
Farr Wind farm	-4.37	**-0.77**	2.55	-4.82	**-1.44**	2.39
Black Law	-7.55	**-0.62**	6.93	-8.37	**-1.07**	6.31
Grise	-7.06	**-0.78**	5.82	-8.76	**-1.93**	5.04
Slieve Rushen	-0.97	**-0.33**	-0.62	-0.91	**-0.62**	-0.7
Lissett	-17.09	**-4.49**	8.41	-19.9	**-6.99**	5.41
Mynydd Clogau	-3.56	**-0.94**	1.52	-4.14	**-1.37**	1.25
Ness Point	-10.9	**-2.6**	6.79	-13.16	**-3.63**	6.05
Westmill	-15.23	**-0.14**	14.37	-19.68	**-3.29**	14.59
Bears Down	-6.4	**-1.73**	2.57	-7.19	**-1.86**	2.63

Table 4-8: Projected annual capacity factor change for selected onshore wind farm locations

4.5.4.1 Projected Change of other Onshore Wind Turbine States

Obviously other wind turbine states are affected by a changing wind climate and it can be beneficial to planners and developers to know what sort of characteristics a wind turbine or wind farm will have at a particular location. Knowledge of how the characteristics may change as a result of wind speed variability due to climate change may also be valuable input to planning and development decisions. See Appendix B-9 to B-12 for further information.

4.6 The Effect of Climate Change on Potential Onshore Resource

The aim of this section is to explore the changes that projected wind speeds will have on the UK potential baseline onshore wind energy resource. This is achieved by applying the projected change values to the baseline capacity factor at each of the wind farm locations discussed in section 4.4.1, weighting the energy output by the installed capacity at each wind farm and adjusting for assumed losses discussed in section 4.3.3.

The impact of the projections on the baseline collective energy output (Figure 4-10) of the wind farm locations (Figure 4-9) are shown in Table 4-9 which contains the values of weighted average capacity factor change values for all included onshore wind farm locations for the 2050s and 2080s. They include the losses discussed in section 4.3.3, and have a scaling factor of 0.8379 relative to values that do not include the losses (Table B-1 in Appendix B).

Scenario	**Projected Aggregate Capacity Factor Change From Baseline (%) – Assuming Losses**												
	ANN	**JAN**	**FEB**	**MAR**	**APR**	**MAY**	**JUN**	**JUL**	**AUG**	**SEP**	**OCT**	**NOV**	**DEC**
Baseline (%)	**34.6**	**41.7**	**40.4**	**40.8**	**35.2**	**31.8**	**30.5**	**26.4**	**25.9**	**34.1**	**36.3**	**38.8**	**40.1**
2050s 10% Probability	32.6	39.8	38.5	39.1	33.8	29.5	28.2	23.8	21.9	31.4	35.0	37.8	39.3
2050s 50% Probability	**34.3**	**41.4**	**39.6**	**40.6**	**34.8**	**31.3**	**30.8**	**26.6**	**24.5**	**33.3**	**36.3**	**39.4**	**40.6**
2050s 90% Probability	36.0	42.8	40.8	41.8	35.8	33.2	33.2	29.3	27.1	35.0	37.5	40.8	41.8
2080s 10% Probability	32.2	39.7	38.4	39.0	33.1	29.0	27.8	23.0	20.8	30.7	35.2	38.2	38.7
2080s 50% Probability	**34.1**	**41.0**	**39.8**	**40.0**	**34.4**	**31.1**	**30.5**	**25.8**	**23.9**	**32.8**	**36.6**	**39.4**	**40.3**
2080s 90% Probability	35.8	42.2	41.0	40.8	35.8	33.2	33.1	28.5	27.0	34.8	37.9	40.6	41.6

Table 4-9: Projected Aggregate Capacity Factor Change from Baseline – assuming losses

Table 4-10 summarises the monthly and annual projected change from baseline for the 2050s and 2080s medium emissions scenario with 50% probability. As can be seen the 2050s shows a 0.55% reduction in generated electricity from wind energy, and the 2080s shows a 1.42% reduction from baseline.

Scenario	**Overall Baseline Energy Output – including losses (GWh)**												
	ANN	**JAN**	**FEB**	**MAR**	**APR**	**MAY**	**JUN**	**JUL**	**AUG**	**SEP**	**OCT**	**NOV**	**DEC**
Baseline	38415	3874	3390	3789	3162	2949	2740	2455	2405	3068	3370	3489	3725
Projected Aggregate Change From Baseline Energy Output – including losses (GWh)													
2050s 50%	-211	-29	-65	-22	-33	-44	31	13	-126	-76	-3	53	48
2080s 50%	-545	-69	-54	-77	-69	-57	4	-60	-184	-121	30	48	18
Percentage Change (%)													
2050s 50%	-0.55	-0.76	-1.92	-0.58	-1.04	-1.5	1.12	0.54	-5.25	-2.47	-0.08	1.51	1.3
2080s 50%	-1.42	-1.79	-1.58	-2.03	-2.18	-1.95	0.15	-2.46	-7.64	-3.93	0.88	1.37	0.48

Table 4-10: Projected Change from Aggregate Baseline Energy Output

Table 4-11 shows just the annual wind energy projection changes for a medium emissions scenario in 2050s and 2080s and includes the 10% and 90% distribution points as well as the 50% distribution midpoint.

Offshore Wind - Future Climate Energy Output – including losses			
Scenario	**Generated (GWh)**	**Change (GWh)**	**Change (%)**
Baseline	**38,415**		
2050s 10% Probability	36,282	-2,133	-5.55%
2050s 50% Probability	38,204	-211	-0.55%
2050s 90% Probability	40,006	1,592	4.14%
2080s 10% Probability	35,852	-2,562	-6.67%
2080s 50% Probability	37,870	-545	-1.42%
2080s 90% Probability	39,763	1,348	3.51%

Table 4-11: Annual Climate Change Values from Baseline Wind Energy Output

In Figure 4-23 the baseline and the 2050s probabilistic onshore wind monthly energy output is shown. As can be seen the 10% and 90% lines envelope the baseline. The 50% probability line shows a clear reduction over much of the year especially in August and September, where the lower seasonal resource looks to reduce even further. November and December show a clear increase in resource.

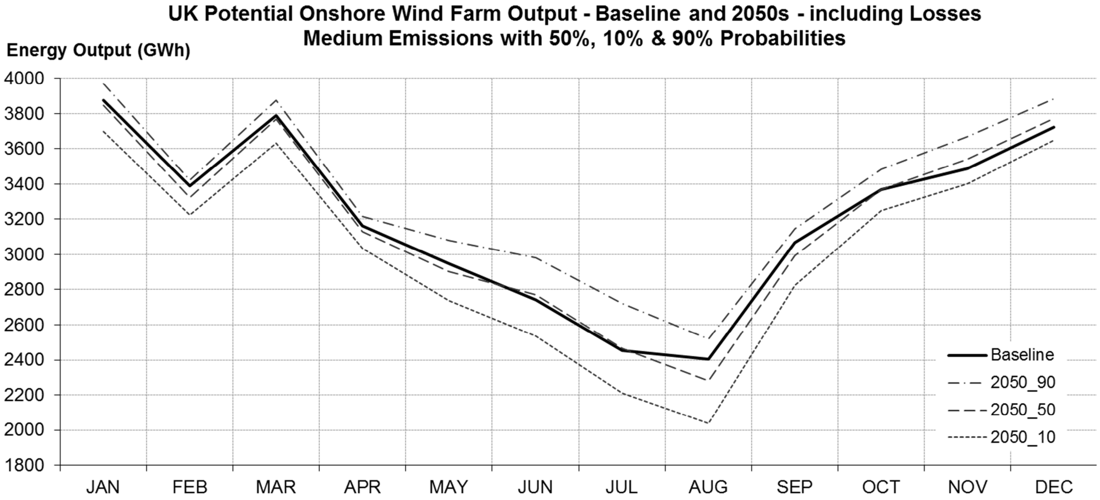


Figure 4-23: 2050s Impact on baseline energy resource scenario

Figure 4-24 shows the baseline and the 2080s probabilistic onshore wind monthly energy output. The characteristics are very similar to those of the 2050s though there is a definite further reduction, especially in August. Both the 2050s and 2080s show a reduction in energy yield throughout the year, the 2050s show an annual change of -4.0% (-10.2%, +1.6%) and the 2080s a change of -5.1% (-11.6%, +0.8%).

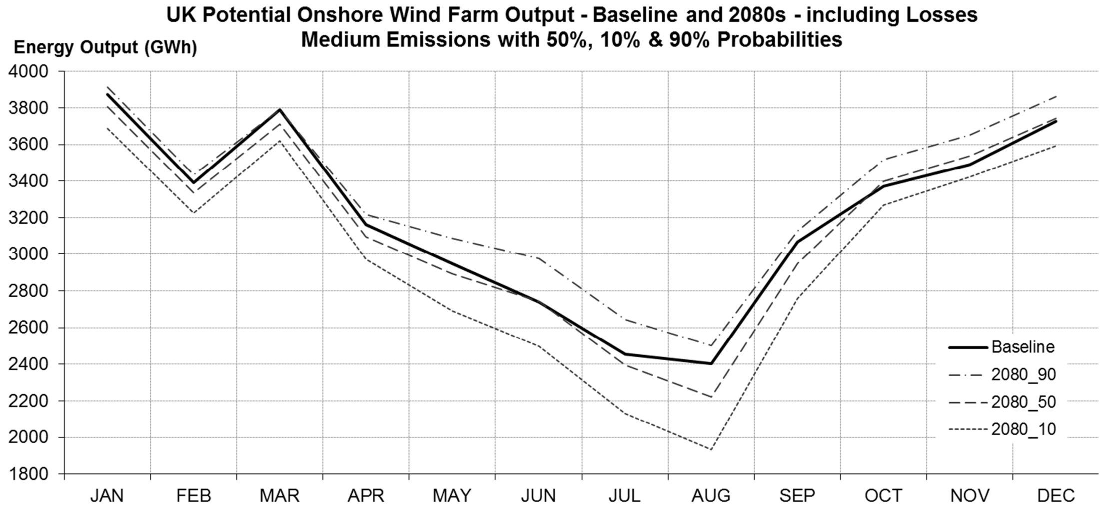


Figure 4-24: 2080s Impact on baseline energy resource scenario

In both the 2050s and 2080s the months with the largest uncertainty are May to August, they are also the lowest yield months. These larger uncertainties are due to a higher proportion of time that turbines are generating but below or just reaching the rated capacity. This is where the turbine energy output is most sensitive to wind speed variability.

4.7 Onshore Wind Summary

Accurate estimates of mean monthly onshore wind power resource has been generated from monthly wind speed data using a Rayleigh distribution and a generic wind turbine power curve. Baseline models of wind speed and wind energy output have been created. Estimations of total UK wind energy output have been created based on the locations and size of all operational and planned wind turbine sites.

The baseline wind speed model is in close agreement with two other UK wind models (EWM & DECC). It appears to be roughly 0.5 m/s higher than both the other models with a RMSE of 1.29 m/s.

The baseline wind energy model with an average capacity factor of 35.1% is 8 percentage points higher than the observed UK average (27.1%) (DUKES 2010). The discrepancies are discussed in section 4.4.1.

HadRM3 wind climate data has been used to show probabilistic climate change impact in per cent change relative from baseline values for the baseline wind speed and wind energy models. Climate change models for wind speed and wind energy have been created.

The 2050s and 2080s appear to indicate slight negative changes in wind speed ranging in the extreme to approximately -5.0% (-10.5% to 0.4%) in the 2050s and -6.9% (-12.8% to -1.0%) in the 2080s.

The overall annual wind energy output from all wind turbine sites in operation and planned is estimated to be in the region of 38.415 TWh for the baseline climate. It is estimated that climate change could change this by -0.55% (-5.6% to 4.1%) for the 2050s and -1.4 (-6.7% to 3.5%) for the 2080s. The future onshore wind energy resource is more seasonally variable. There are slight increases in winter months, when resource is at its best; and slight resource decreases in some summer months.

Table 4-12 shows the onshore wind capacity factor values estimated in this chapter. These figures are used in chapters 7 and 8 when calculating levelised cost values for onshore wind.

Technology	Climate Scenario						
	Baseline	2050 10%	2050 50%	2050 90%	2080 10%	2080 50%	2080 90%
Onshore Wind	35.1	33.2	35.0	36.6	32.8	34.6	36.4

Table 4-12: Onshore wind capacity factor values

5 Offshore Wind Power

5.1 Introduction

The main objective of this chapter is to assess the baseline UK offshore wind resource and investigate the impact climate change could have on the resource. It uses the Hadley Centre RCM HadRM3 (Met Office 2008) model to assess the baseline resource and the projected change from the baseline wind speeds.

The yellow blocks in the thesis flowchart (Figure 5-1) signify the areas of the thesis connected with this chapter.

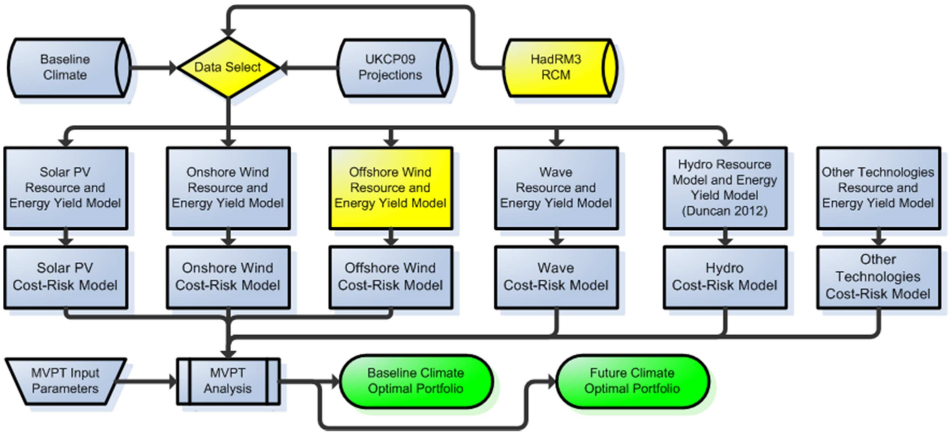


Figure 5-1: Thesis flowchart and offshore wind resource blocks

5.1.1 Chapter Overview

A UK baseline offshore wind speed model was created using averaged monthly wind speed data from the HadRM3 data set. Ideally, the baseline model would use actual measured data from a large network of locations over a 30 year time period, as with the wind speed baseline model for onshore wind (Chapter 4); but wind speed data at offshore locations is much less common than onshore and can be inconsistent.

The baseline offshore wind energy model was generated by converting the 30 year averaged monthly HadRM3 wind speed data from its 10m height to an 80m hub height. The data was then fitted to a Rayleigh distribution and fitted to the power output curve of a typical 3 MW wind turbine in the same manner as described for onshore wind. Using the HadRM3 daily data to provide the distribution was considered, which in retrospect may have given a better distribution, however, it was decided to follow the same method as for onshore wind.

To validate the wind and energy baseline model they were compared with data from other sources. Baseline wind speeds compared favourably with wind speeds from the UK Marine Renewable Energy Resource Atlas and recorded wind speeds at 4 operating wind farms. Baseline wind energy values were compared with output from 4 operating wind farms.

A UK offshore wind farm baseline resource model was created to closely reflect the actual present and future distribution of wind farms and both individual and collective energy resource and generation characteristics. The actual positions and sizes of all operating and potential future (in-construction, consented and in planning) offshore wind farm locations were projected onto the baseline wind energy output model. Monthly averaged output for each location were collected and accumulated to complete the UK offshore wind farm resource model.

The generation of 2050s and 2080s probabilistic wind speed projections for a medium emissions scenario using the HadRM3 data uses the same method as used for onshore wind and is described in Chapter 4. Projected wind speed and energy models for the 2050s and 2080s were created in the same way as described for the baseline models. The projected climate variability of wind speed wind energy and the UK offshore wind farm resource model was explored by comparing the baseline data with the projected future data.

5.2 Baseline Resource

5.2.1 Creation of UK offshore baseline wind model

The HadRM3 data set was used as the source of modelled wind speed data to generate the UK offshore wind speed baseline model as it was not possible to generate an accurate UK baseline offshore wind speed model from actual observed offshore wind speed data. Locations in UK waters with observed wind speeds over a long period of time are sparse and the data can be inconsistent. Anemometers can be sited on structures such as oil and gas platforms, buoys and various other ocean vessels, there can be inconsistencies in the anemometer installation height and surrounding environment which in turn can cause measurement inaccuracies.

The Met Office observed gridded data sets, used in Chapter 4 to create the onshore baseline wind speed model, could not be used to create the offshore wind model as the data set only covers onshore locations, therefore, offshore daily wind speeds were extracted from the HadRM3 data set over the baseline time period (1961-1990) and processed in the same way as described for the UK onshore baseline wind model in Section 4.2.1. The HadRM3 onshore wind biasing issues for wind speeds over mountainous and flat land regions, mentioned in Chapter 4 do not exist for offshore locations (Sexton *et al.* 2010b).

Figure 5-2 shows the baseline offshore wind speed at a hub height of 80m. The average baseline seasonal wind speeds vary quite dramatically and it can be seen that winter wind speeds can be up to 50% higher in winter months than summer. The offshore wind speeds are also less variable and generally higher than the onshore baseline wind speeds. Another generally accepted advantage of offshore wind over wind at onshore locations is there is much less turbulence due to the sea being generally flat.

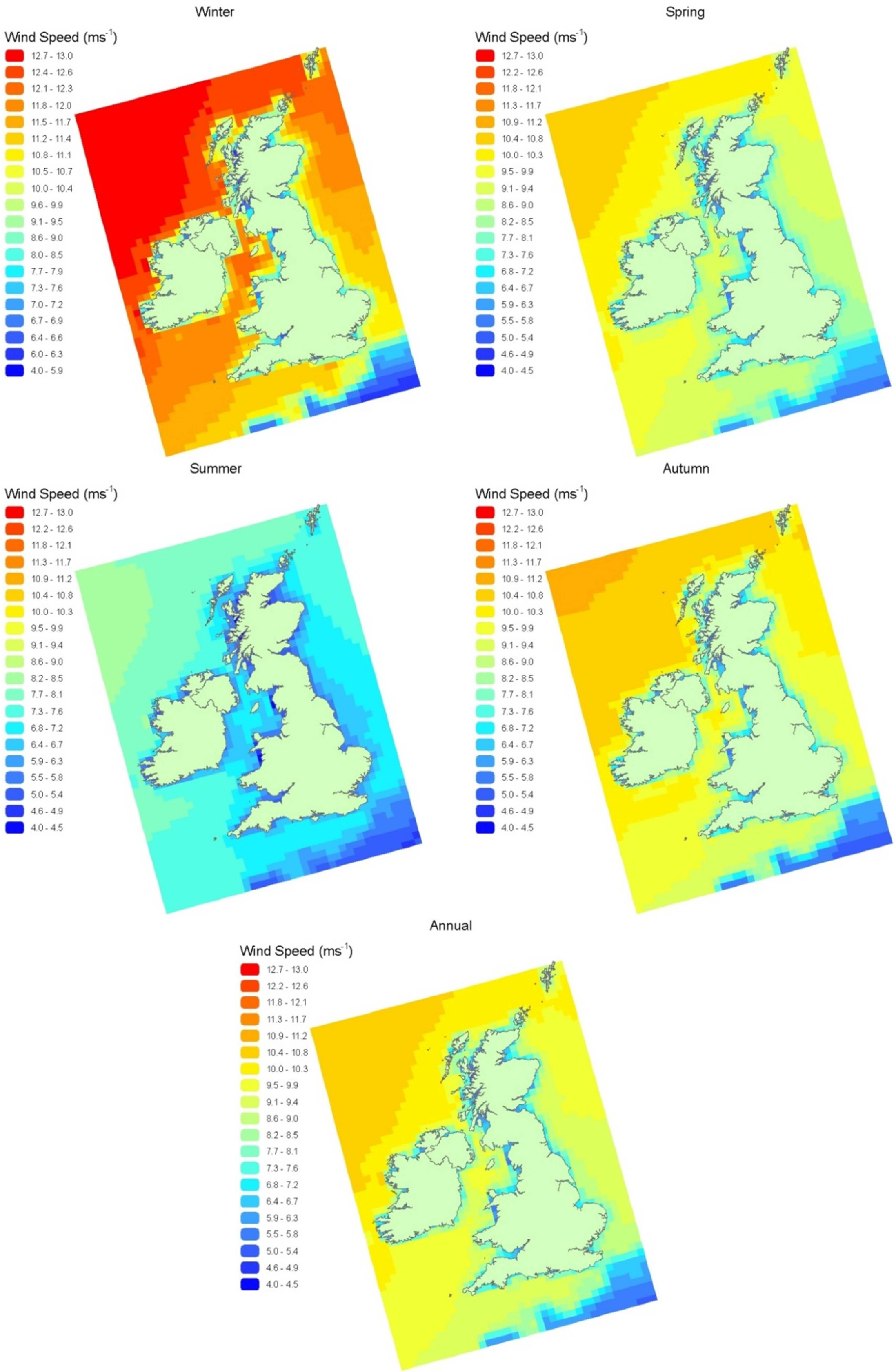


Figure 5-2: UK baseline offshore average wind speed at 80m height

5.2.2 Creation of UK offshore baseline wind energy model

The offshore baseline wind energy model was developed from the average wind speed data (which used the data to generate the UK offshore wind baseline model). Each cell of the 30 years of gridded average monthly wind speed data was fitted to a Rayleigh distribution and the distribution output then fitted to the Vestas V90 3 MW wind turbine in the same way as described for onshore wind.

Figure 5-3 shows the seasonal and annual offshore wind energy baseline capacity factors. The figures assume 100% availability of the wind turbine. In winter there is enough wind speed to provide capacity factors in excess of 50% at the majority of locations. In other months there appears to be higher resource in north westerly regions, which gradually reduce towards the south east or coastal locations. The lowest capacity factors are seen close to coastlines.

One interesting observation when looking at winter months on a different scale (see Figure 5-4) is that locations further from shore in the North West, which have the highest wind speed, clearly have a lower capacity factor than other far from shore locations. This is due to a larger proportion of time in which the generic wind turbine profile (Vestas V90 3MW) is in the above cut out state due to the higher wind speeds. This is confirmed in Figure 5-5 where locations in the North-West spend up to 15% of time in winter months and up to 7.2% annually in the above cut out state, under the baseline wind speed conditions. The larger proportion of cut-out time in winter months demonstrates the need to match the characteristics of wind turbine characteristics to the location’s resource. For example, any future plans to locate a wind farm in the high resource areas of the north-west would benefit from a wind turbine design tuned to the particular resource at that location and benefit from an increased cut-out speed and probably a larger capacity than the model used in this study. However, the increased energy yield would need to outweigh the additional turbine costs.

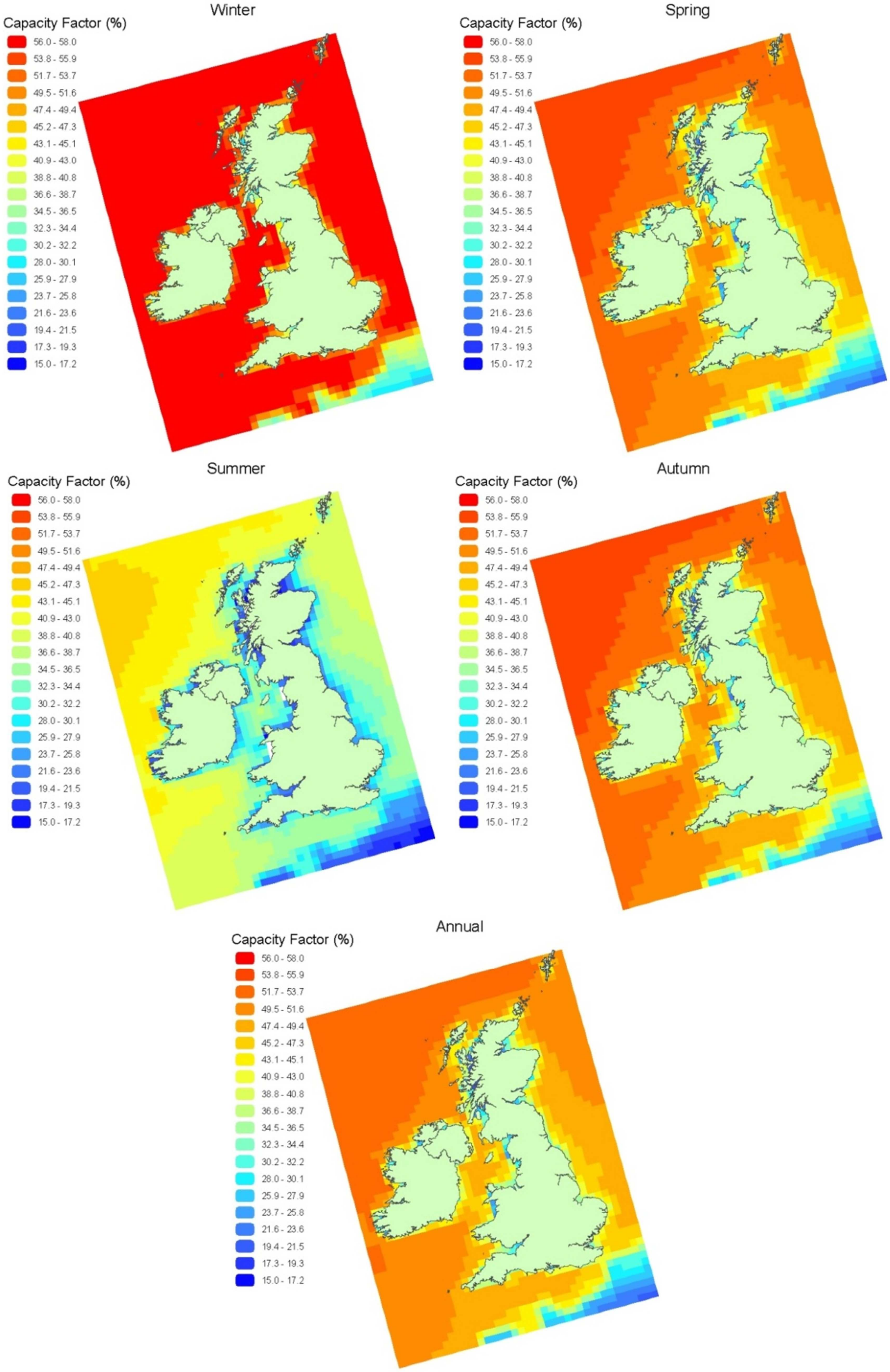


Figure 5-3: Seasonal baseline capacity factors

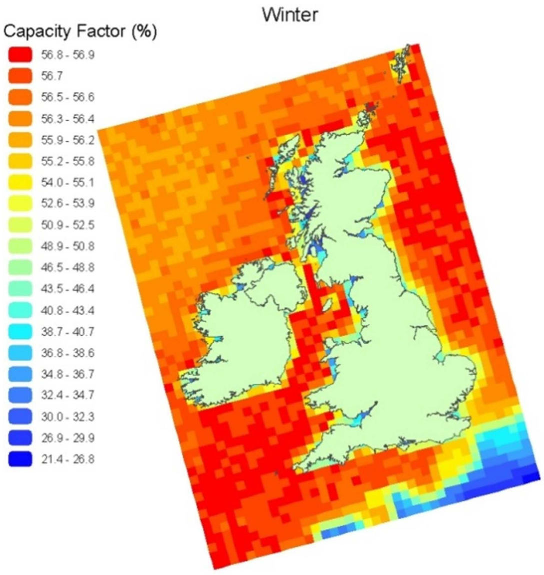


Figure 5-4: Winter baseline capacity factors – different scale to highlight lower capacity factor in north-west

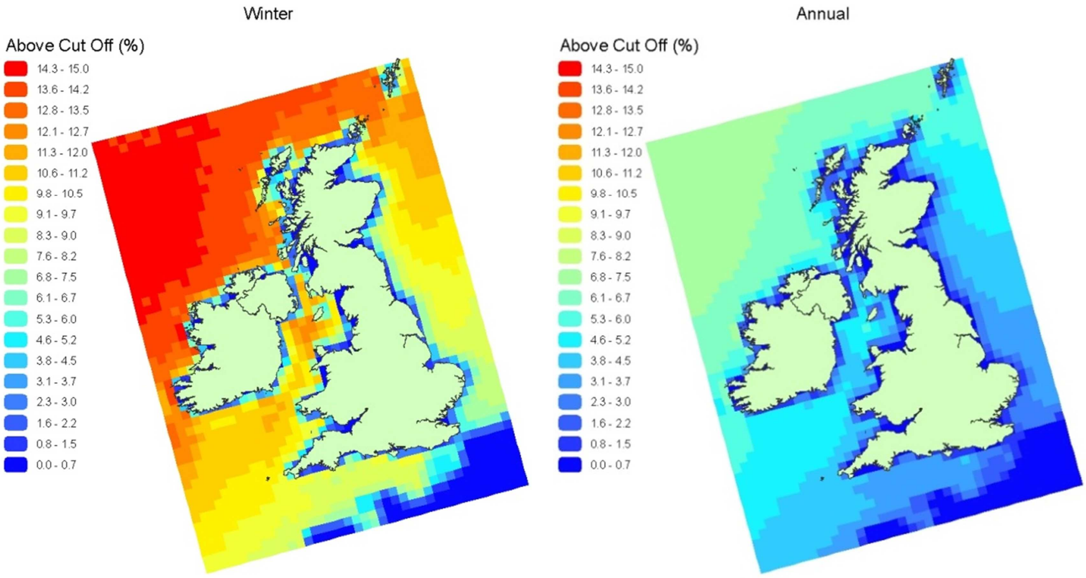
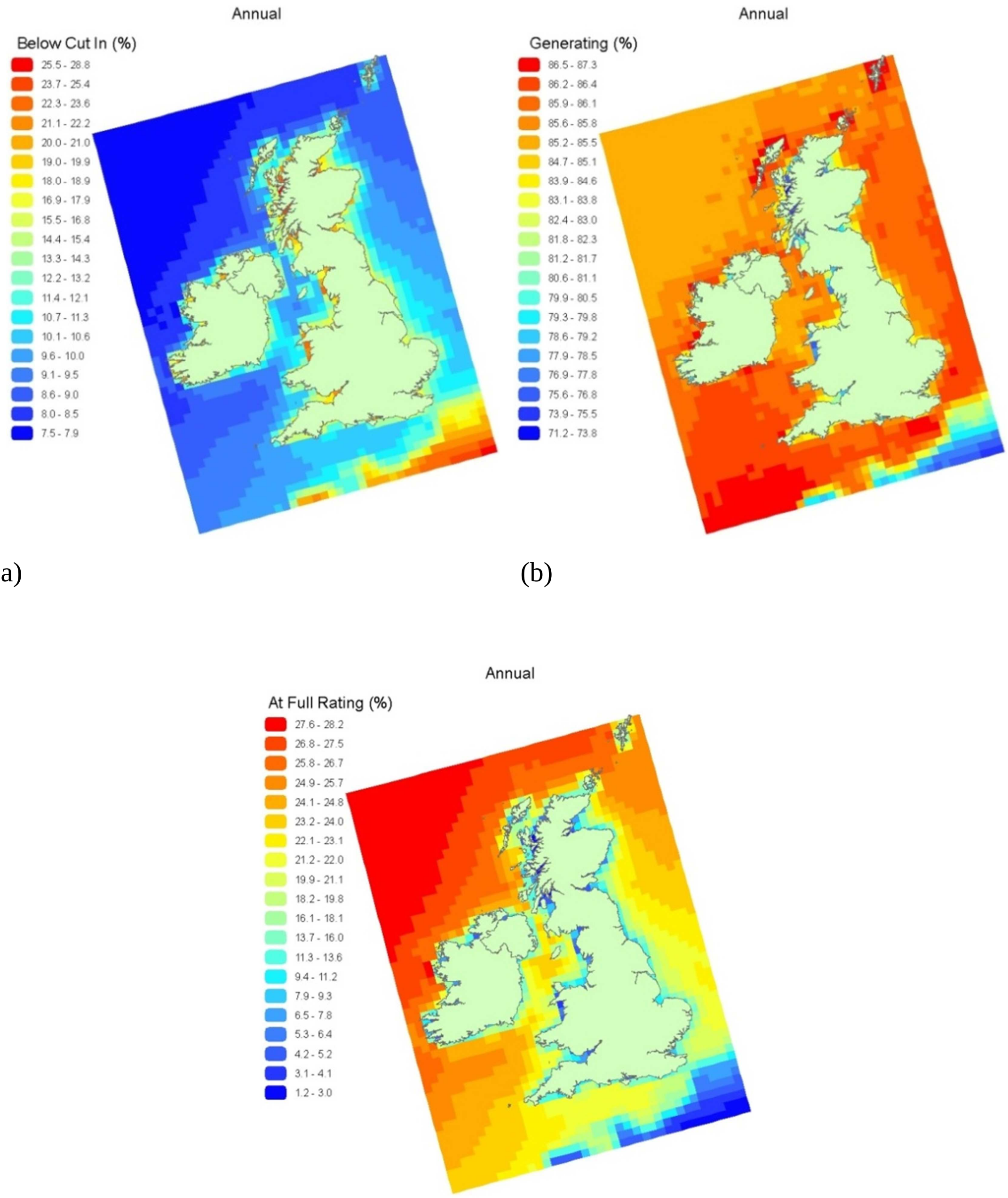


Figure 5-5: Percentage of time in above cut out state for winter months and annually

Other wind energy baseline parameters of interest are shown in Figure 5-6, the annual time spent cut in is below 10% of the time for most offshore locations with very high proportions of time in the ‘generating’ and at ‘full rating’ state. The North-west offshore locations spend less time generating than other offshore locations, mostly due to having a high proportion of above cut out time; however, a large proportion of the time generating is at ‘full rating’ and so ends up being the location with the highest overall capacity factor.



(a) (b)

(c)

Figure 5-6: Other Baseline Resource Parameters: (a) annual percent time below cut in, (b) annual percent time between cut in and cut out, (c) annual percent time at full rating.

5.2.2.1 Uncertainties

The data and method to generator baseline offshore wind and energy models contain a number of uncertainties. The wind speed data is from modelled HadRM3 output which will contain errors compared to observed values. There are uncertainties due to the 25km resolution of the HadRM3 gridded data which will not capture all the wind flow detail. The roughness length relating to a ‘calm sea’ was assumed and this will add additional error in periods of rougher seas. A standard Rayleigh wind distribution was assumed for all locations, this is an acceptable method when working with such a large area; however it may add large uncertainties in locations with different wind distributions. There has been a generic power curve assumed for the power conversion which will add additional error. The wind to power conversion process does not capture any turbulence issues.

5.3 Data Analysis and Validation

The aim of this section is to compare the modelled wind speed and capacity factor values with actual observed values.

5.3.1 Wind Resource

The HadRM3 generated baseline monthly average wind speed data has been compared to wind data used in the UK Marine Renewable Energy Resource Atlas (BERR 2008a) which is derived from met office weather forecast models. Wind speed output from the two data sets compare very favourably with each other.

Figure 5-7 shows wind data from both data sets. Key wind farm locations have been shown for reference as red dots. The BERR Atlas wind speeds were transformed from 100m to 80m height to match the HadRM3 baseline height. Wind speeds are largely very closely matched between the two models. One difference worth noting is that the BERR Atlas shows wind speeds in the far north-west to be up to around 10% higher than HadRM3 values. The BERR Atlas technical report examines these higher than expected wind speeds and comments on two possible explanations: they may be real and be part of a storm track caused by topographic features and winds naturally travelling between Iceland and UK; or they may be caused by a model artefact.

A further point worth mentioning is the HadRM3 wind speed values are averaged over a 30 year period (1961-1990) which should capture more long term wind climate characteristics than the BERR Atlas data, which is averaged over a 7 year period (June 2000- May 2007) and therefore more susceptible to inter-annual biasing.

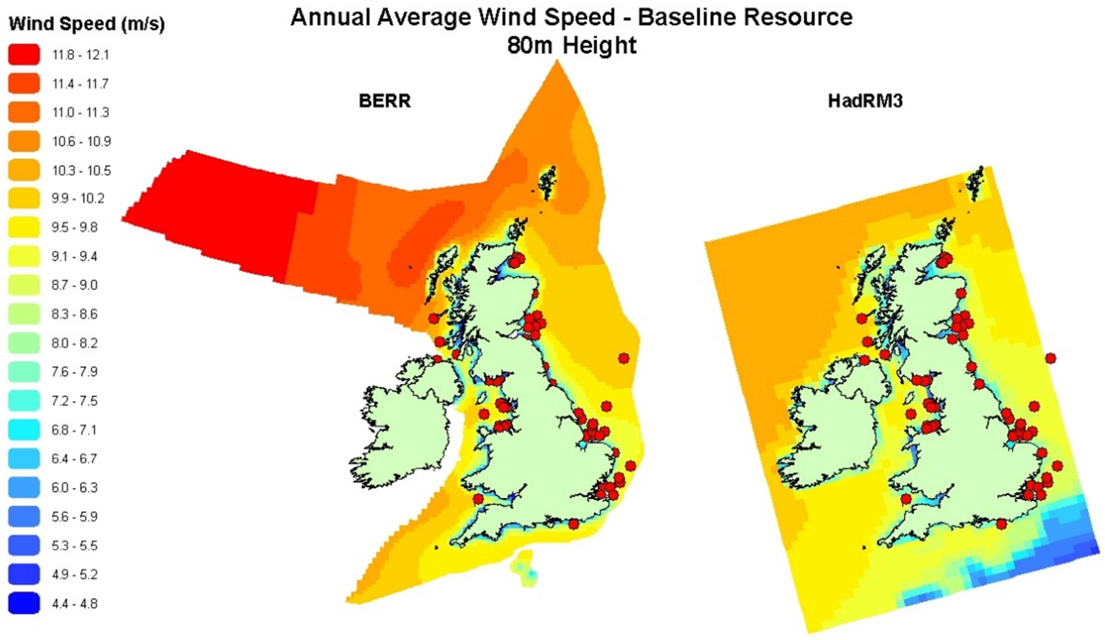


Figure 5-7: Comparing BERR average wind speeds (left) with the HadRM3 generated baseline wind speeds (right); locals of existing and planned wind farms shown as dots

Annual average wind speeds for both BERR Atlas and HadRM3 at offshore wind farm locations are shown in Figure 5-8. The values match well: the RMSE is 0.56 m/s and on average the HadRM3 wind speeds are only 0.08 m/s lower than the BERR Atlas value.

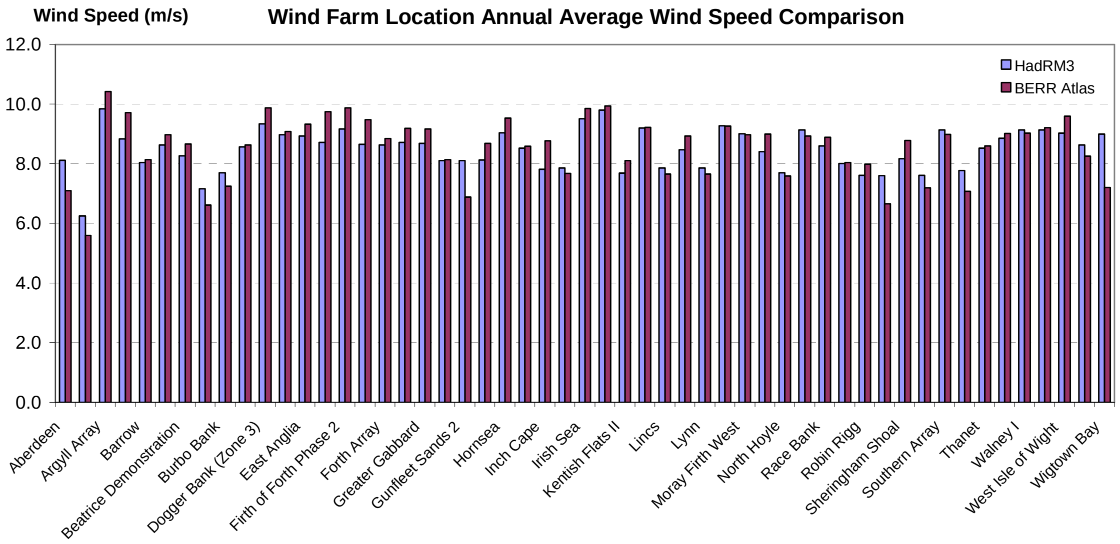


Figure 5-8: Comparing BERR Atlas and HadRM3 baseline annual values at wind farm locations

5.3.2 Observations at Operational Offshore Wind Farms

There is limited historical data on the performance of operational offshore wind farms. One of the best sources of information is the DECC 'Offshore Wind Capital Grants Scheme' reports which contains in-depth information for 4 Offshore Wind Farms over 4 year periods, as shown in Table 5-1.

Barrow	July 2006- June 2008
Kentish flats	January 2006 – December 2008
North Hoyle	July 2004 – June 2007
Scroby Sands	January 2005-December 2007

Table 5-1: Wind Farms with Offshore Capital Grants Scheme Reports (DECC 2004-2009)

5.3.2.1 Wind Speed Comparison

Figure 5-9 and Figure 5-10, show actual observed wind speeds for North Hoyle and Kentish Flats offshore wind farm locations and time periods shown in Table 5-1. Also shown are the HadRM3 baseline and BERR Atlas wind speeds for the location. Figures C-1 and C-2 in Appendix C show Barrow and Scroby Sands. The very close match between the HadRM3 baseline and BERR Atlas wind speeds are very evident for all locations. The actual observed wind speeds are only averaged over each month and so there is more variability as they do not capture the long term intra-annual and annual average wind speed variability, like the HadRM3 baseline wind speeds which are averaged over 30 years. However, for all four locations it is clear that the observed values have characteristics similar to the modelled wind speeds though there would need to be a larger time period of observed wind speeds to comment any further on the match. Wind speed differences between wind farm observed values and the modelled baseline wind speed values are shown in Table 5-2.

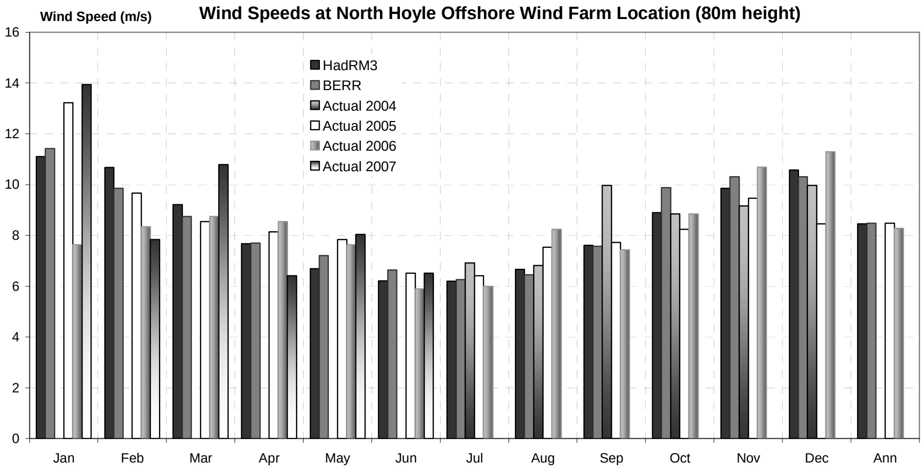


Figure 5-9: Wind Speed Comparison of North Hoyle Offshore Wind Farm Location

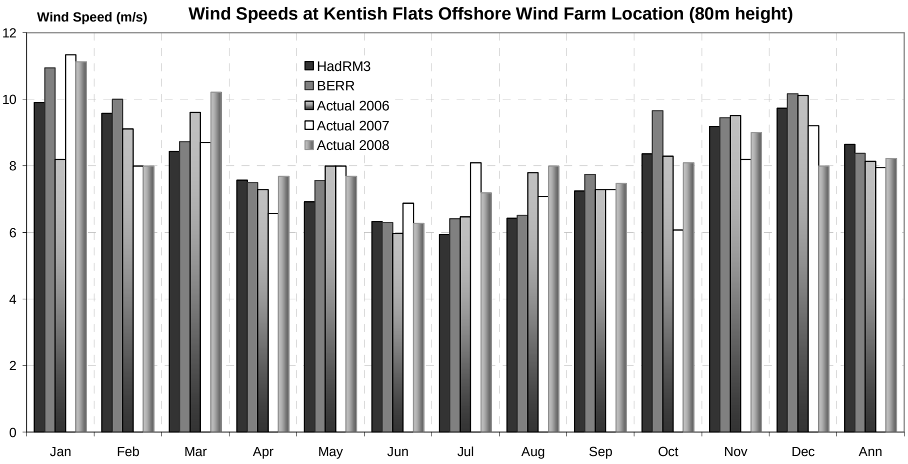


Figure 5-10: Wind Speed Comparison of Kentish Flats Offshore Wind Farm Location

Wind Farm	Typical difference from HadRM3	Average offset from HadRM3
Barrow Banks	+/- 17.0 %	+1.2 m/s
Scroby Sands	+/- 13.3 %	-0.7 m/s
North Hoyle	+/- 9.6 %	+0.1 m/s
Kentish Flats	+/- 10.7 %	+0.1 m/s

Table 5-2: Wind Speed Comparison – Modelled Baseline to Observed Wind Farm Values

5.3.2.2 Capacity Factor Comparison

The aim of this section is to investigate average wind speed to capacity factor characteristics for both the modelled baseline and actual reported wind speed and capacity factor values for the 4 wind farms. Figure 5-11 shows a scatter and polynomial plot of the modelled baseline (HadRM3) average monthly wind speed and the resulting modelled capacity factor. All offshore HadRM3 grid cells have been used to create the plot and this allows extrapolation of the relationship between modelled average wind speed and capacity factor over the UK.

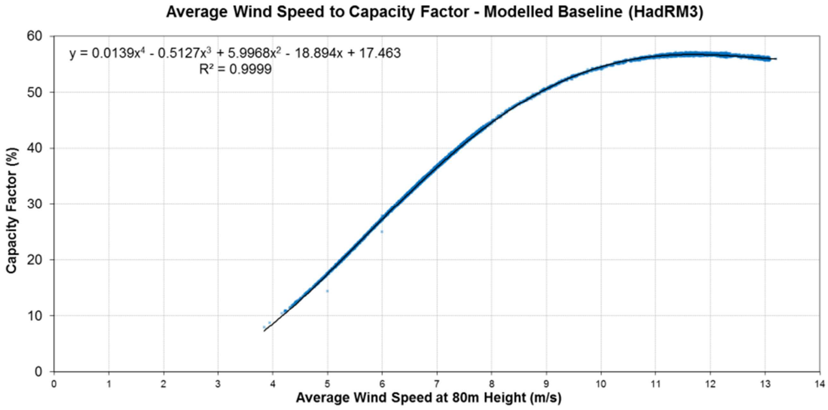


Figure 5-11: Wind Speed to Capacity Factor Plot of Modelled Data

Figure 5-12 shows the modelled baseline plot as in Figure 5-11 and also all the reported values for Barrow, Scroby Sands, North Hoyle and Kentish Flats Offshore Wind Farms. The reported capacity factor values have been factored up using the reported wind farm availability values (DECC 2004-2009) so they are comparable with the modelled values which assume wind farms have 100% availability. There were some availability issues with some of the wind farms. A few extreme outlying data points were assumed to be mis-reads and removed from the analysis.

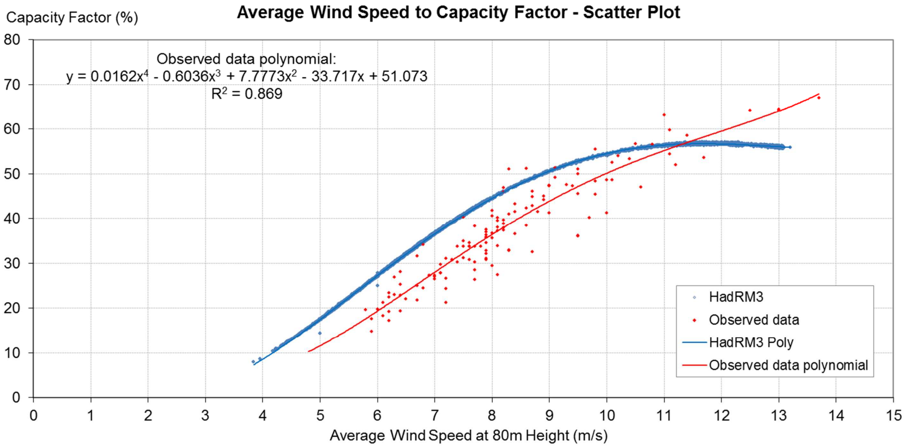


Figure 5-12: Comparing Trend lines of HadRM3 to all available observed wind farm data

As can be seen, the observed data polynomial does not tail off like the modelled data at average wind speeds above approximately 10m/s. The real data also has capacity factor values approximately 6-8% lower than the modelled data for much of the wind speed range. There are several potential explanations why the modelled characteristics are different to the observed characteristics:

- The observed data is monthly averaged over a maximum of only 3 years for only 4 locations and of too small a sample to capture any average wind speed to capacity factor relationship. This is particularly true in the region of higher average wind speeds where there are only a handful of points over 11 m/s, and this lack of data points is likely to be the reason for the lack of tail off being captured in the observed polynomial.

- The modelled data used a standard Rayleigh distribution for all locations whereas each specific wind farm location would have its own specific wind distribution characteristics. The data does indicate that the Rayleigh distribution may have a wider distribution than the real distribution, and so more frequent higher wind speeds than actually seen, leading to more time above the cut out and causing the flattening off above 10m/s.

- The modelled data does not account for ‘array loss’ within a wind farm array.
- The modelled wind speed data has been referenced to a hub height of 80m, whereas the observed data at the four locations have actual hub heights of 75m, 70m, 70m and 65m, and would have slightly lower wind resource due to surface roughness (see section 4.2).

5.3.3 Wind Energy Losses

This section explores wind energy losses such as periods of unavailability for planned and unplanned maintenance, array losses, cable losses between the wind farm and shore, and assumes typical values to apply to the modelled baseline energy values so they more closely reflect observed data.

5.3.3.1 Wind Turbine Availability

There are three different types of availability discussed in the DECC 2004-2009 reports. Technical availability is the percentage of time the wind farm is available for generating electricity. Figure 5-13 shows the technical availability of the 4 wind farms featured in the DECC 2004-2009 reports. Much of the typical values of availability lie in the region of 85-90% but there are periods of much lower values:

Barrow had periods of very low availability between late 2006 and late 2007 due to several non-planned maintenance issues, such as the replacement of all gearboxes. North Hoyle and Scroby Sands also suffered from lower than expected availability around the same time from similar issues.

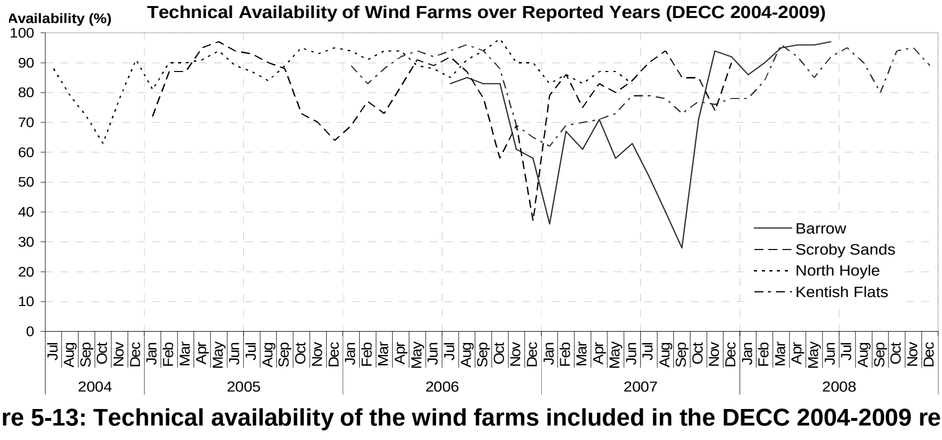


Figure 5-13: Technical availability of the wind farms included in the DECC 2004-2009 reports

The average availability of the four wind farms over the reported period (DECC 2004-2009) is shown in Table 5-3. These values are lower than anticipated by the wind farm operators and are largely due to issues that go hand in hand with an emerging technology such as unproven designs and availability of specialist equipment.

Wind Farm	Barrow	Scroby Sands	North Hoyle	Kentish Flats	**Total**
Average Availability (%)	72.8	81.0	87.7	83.3	**81.2**

Table 5-3: Average Offshore Wind Farm Availability (DECC 2004-2009)

For the analysis in this thesis an overall wind farm availability assumption of 95% will be used. This takes into account the information above and basing it on the availability once the emerging technology has matured. Also taken into account is the assumption that planned maintenance down-time would be performed in times of low wind speeds. It compares with a value of 97% commonly quoted by developers.

5.3.3.2 Wind Farm Array Wake and Electrical Losses

Taking into account the comparisons of modelled and observed capacity factor in Section 5.3.2.2 and other sources discussing wake loss in offshore wind farm arrays (Barthelmie *et al.* 2007, 2009, 2010; Phillips *et al.* 2010), which vary considerably from roughly 3% to 20%, it would be fair to assume array wake losses in the region of 10%.

Reported offshore wind farm transformer and cable electrical losses in the Capital Grants Scheme reports range from 0.5% to 2.6% (DECC 2004-2009). A 2.0% loss will be assumed.

5.4 Technology Deployment

In the UK there are presently over 13 operational offshore wind farms with their total installed capacity exceeding 1.3 GW and these numbers are set to grow substantially: There are a further 7 wind farms (2.2 GW) in construction, 5 wind farms (1.8 GW) consented, and a further 4 wind farm projects (2.0 GW) in planning (Renewable UK 2011).

The majority of operational offshore wind farms are from the Crown Estate's 'Round 1' leasing of the UK sea bed (December 2000), which introduced approximately 1 GW of near-shore installed capacity. A second round of leasing (Round 2) was announced in 2003 which allowed 15 projects and a total installed capacity of around 7 GW to apply for leases (The Crown Estate 2011a). Round 3 is much more ambitious than the previous two rounds. In deeper water, further from shore and with an aim to deliver 25% of the UK's electricity demand by 2020, it was announced in 2008. The successful bidders, with a total installed capacity of 32.2 GW were announced in 2010 (The Crown Estate 2011b). In addition to the Round 3 allocations there was a further allocation of "Scottish Exclusivity" sites with a total installed capacity of over 6 GW at 9 different locations (The Crown Estate 2011c).

5.4.1 Deployment Method

For this study, the method used to evaluate the present UK offshore wind energy resource characteristics was to identify all locations that are operational, in construction, consented, and in planning and to include any not so far included from the Crown Estate (Round 1, 2 and 3) and Scottish Exclusivity leased locations.

A total of 54 offshore wind farm locations and a total installed capacity in the region of 47.8 GW were used to explore the baseline offshore wind energy resource characteristics. The locations of each round of leasing are shown in Figure 5-14.

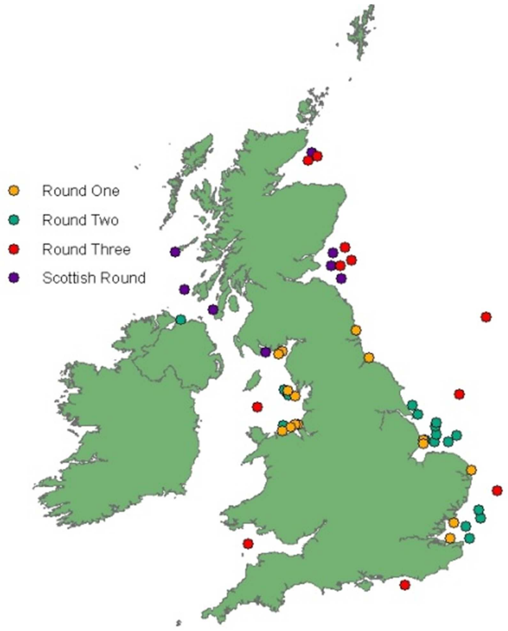


Figure 5-14: Locations of Wind Farms for Different Leasing Rounds

All the wind farms locations shown in Figure 5-14 were used to calculate the potential UK energy output. The capacity factor values for each location were identified from the baseline wind energy model and the baseline energy outputs were calculated based on the capacity factor and installed capacity at each of the locations.

5.4.2 A closer look at some offshore wind farm locations

This section explores several operating offshore wind farms and some locations of potential future wind farms. The reported capacity factor values of operational wind farms used in this section are from the Renewable Energy Foundation database of renewables obligation generators (REF 2011). The database includes the observed capacity factor values of each wind farm since becoming operational. Unfortunately other useful monthly parameters such as observed wind speed and availability of the wind farm is not included in the database and so there is limited scope for analysis of comparing modelled against observed values.

North Hoyle wind farm is discussed in the following sub-section. It has been chosen for discussion as it is one of the longest operational wind farms in the UK and has a reasonably long time series of reported monthly capacity factor values. It is also one of the wind farms with Offshore Wind Capital Grants Scheme Reports (BERR 2004-2009) which have extensive additional operating information. Barrow, Scroby Sands, and Kentish Flats are also discussed in Appendix C.1 to C.3.

5.4.2.1 North Hoyle Offshore Wind Farm

North Hoyle has been in production since late 2003 and consists of 30 Vestas V80 2 MW wind turbines at a hub height of 65m. Figure 5-15 shows the location of North Hoyle Wind Farm within the baseline gridded energy model showing capacity factor. Each cell is 25km^2. The cell which contains North Hoyle (X) and 3 other adjacent cells are highlighted. Figure 5-16 shows the capacity factor actual average (Real Avg) and model average for the North Hoyle site. The actual average is averaged over three operational years and the spread over those years (2008-2010) is indicated by bars. The model average is the value at location X average (Model Avg). There are too few samples of measured data for the average to show any long term characteristics but the modelled baseline values are indicative of the actual values; the 3 years characteristics approach the 30 year modelled baseline characteristics.

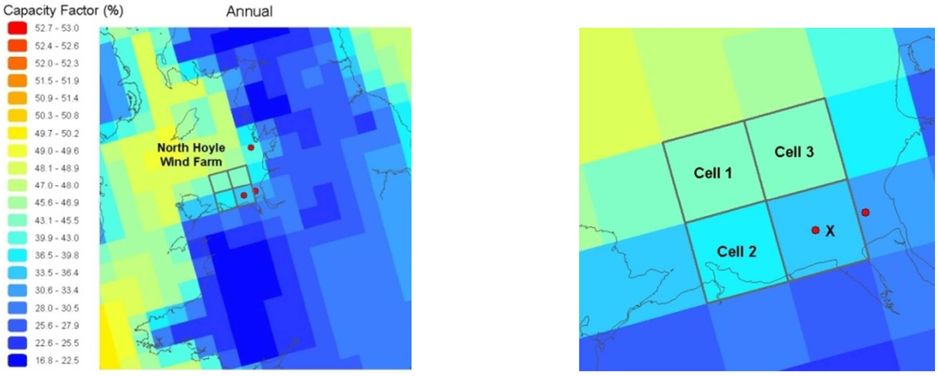


Figure 5-15: Location of North Hoyle Offshore Farm on 25km baseline gridded capacity factor model

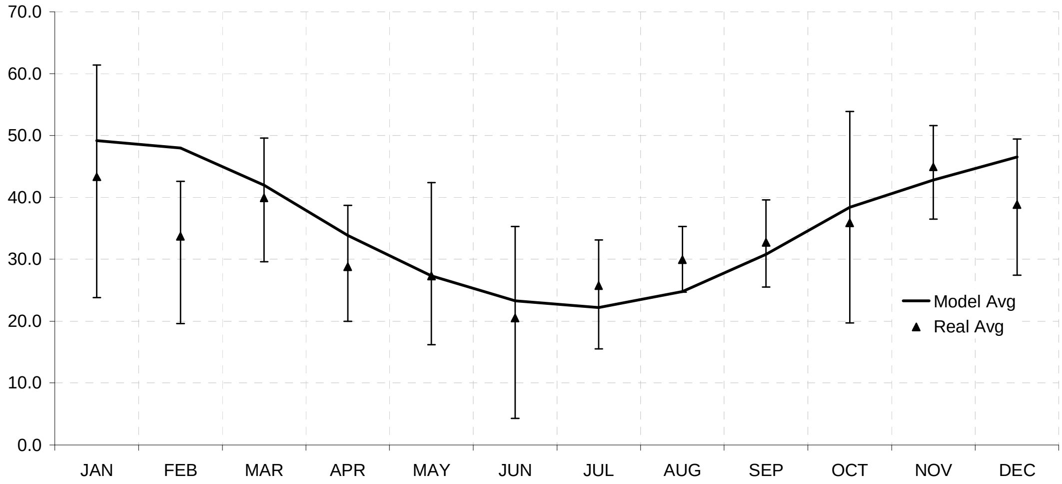


Figure 5-16: Actual capacity factor data and modelled baseline capacity factor

5.4.2.2 Round 3 Zones

The recently announced third round allocations of 9 offshore zones are shown in Figure 5-17 and Figure 5-18 with corresponding modelled baseline monthly capacity factor values shown in Figure 5-19. In Figure 5-20 the modelled annual capacity factors are shown. The capacity factor values are an average value of all cells the wind farms are located in. They assume no losses. One interesting observation is that the further offshore locations, such as Dogger Bank, have higher capacity factor values than zones closer to shore; however, it should also be noted that increased costs associated with depth and distance from shore will counter at least some of the higher resource.

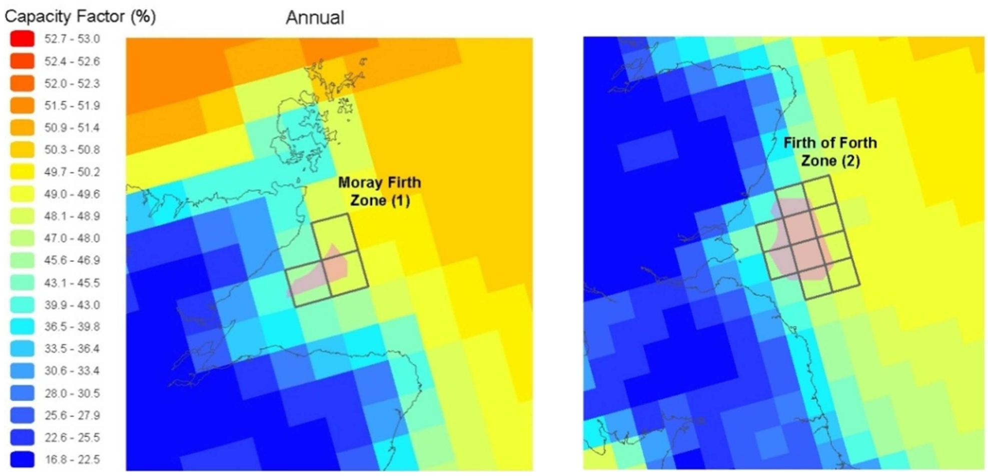


Figure 5-17: Location of Round 3 Zones 1 & 2

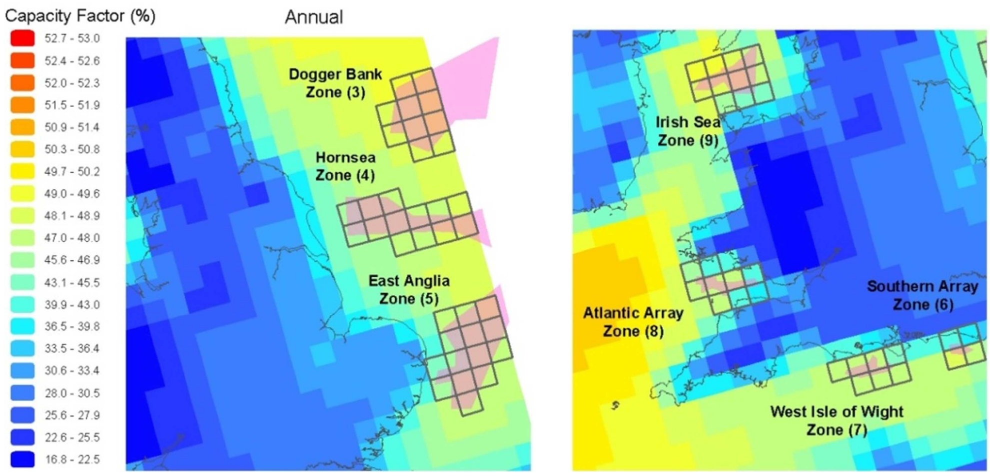


Figure 5-18: Location of Round 3 Zones 3, 4, 5, 6, 7, 8 & 9

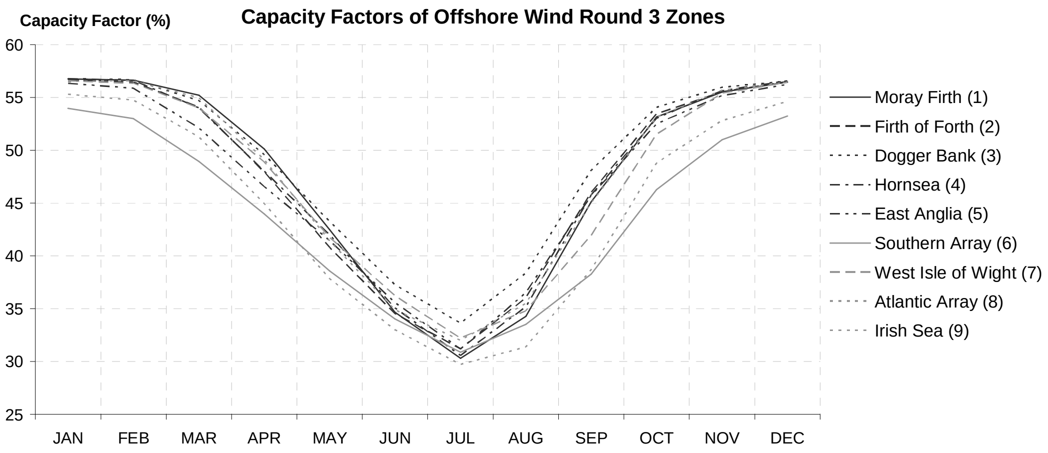


Figure 5-19: Round 3 Zones - modelled baseline capacity factor

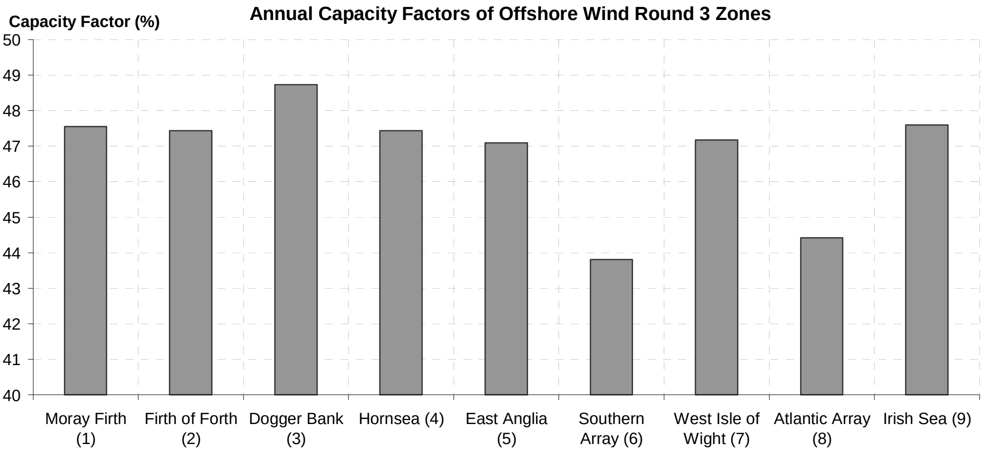


Figure 5-20: Round 3 Zones - Annual modelled baseline capacity factor

5.4.2.3 Scottish Exclusivity Award Zones

The Scottish exclusivity zones are shown in Figure 5-21, the modelled baseline monthly capacity factor values in Figure 5-22 and modelled annual values in Figure 5-23.

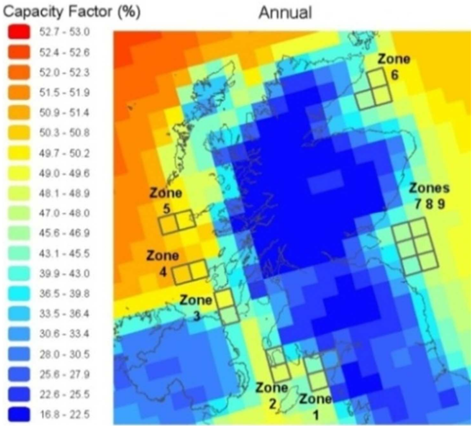


Figure 5-21: Location of Scottish Exclusivity Zones

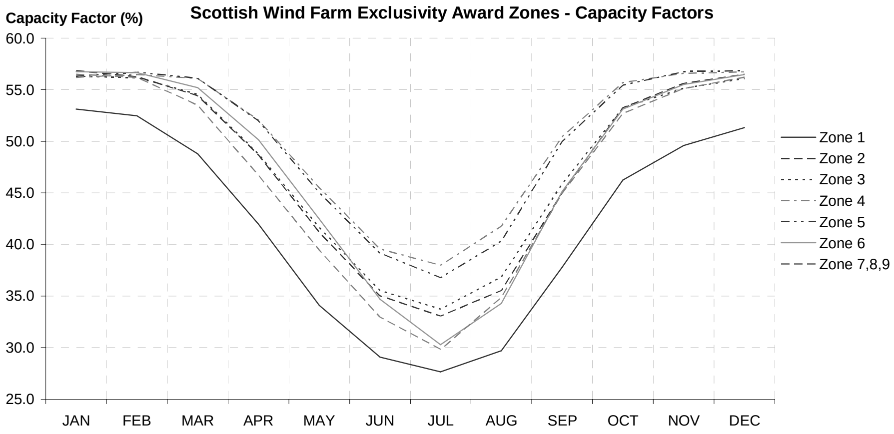


Figure 5-22: Scottish Exclusivity Zones - modelled baseline capacity factor

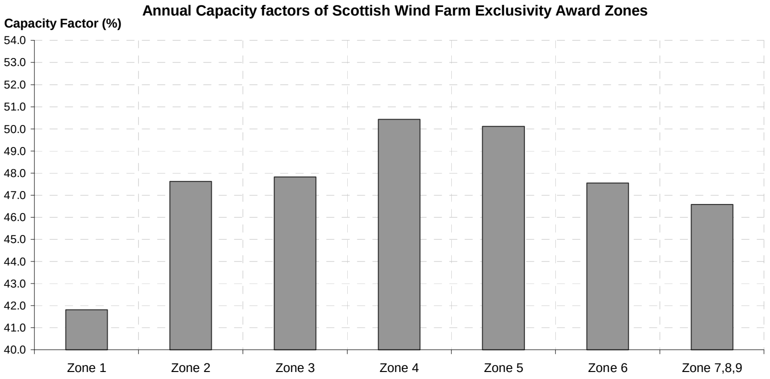


Figure 5-23: Scottish Exclusivity Zones - Annual modelled baseline capacity factor

5.5 UK Potential Offshore Resource

The potential UK offshore wind farm resource was estimated by using all the potential wind farms sites and sizes to calculate the potential UK energy output as modelled by HadRM3. The monthly average capacity factors at each location (shown in Tables C-1 to C-4 in Appendix C) were extracted from the baseline wind energy model as described in section 5.2.2. The overall capacity factor values are shown in Table 5-4 weighted by the installed capacity at each location. Also shown are values with loss assumptions included, which are also shown in Figure 5-24.

The overall installed capacity comes to a total of 47.78 GW. The total baseline annual energy output is 196 TWh without losses and 164 TWh with losses.

Overall Baseline Capacity Factors (%) and Energy Output (TWh)													
	ANN	**JAN**	**FEB**	**MAR**	**APR**	**MAY**	**JUN**	**JUL**	**AUG**	**SEP**	**OCT**	**NOV**	**DEC**
Assuming No Losses													
C.F.	46.8	56.2	55.9	53.1	47.3	40.9	34.7	31.1	35.4	44.9	52.2	54.9	55.9
Energy	196.00	19.99	17.96	18.89	16.29	14.53	11.94	11.04	12.60	15.43	18.56	18.89	19.89
With Assumed Losses													
C.F.	39.2	47.1	46.8	44.5	39.6	34.3	29.1	26.1	29.7	37.6	43.7	46.0	46.8
Energy	164.24	16.75	15.05	15.83	13.65	12.17	10.00	9.26	10.56	12.93	15.56	15.83	16.67

Table 5-4: Baseline Capacity Factors - Aggregate Total

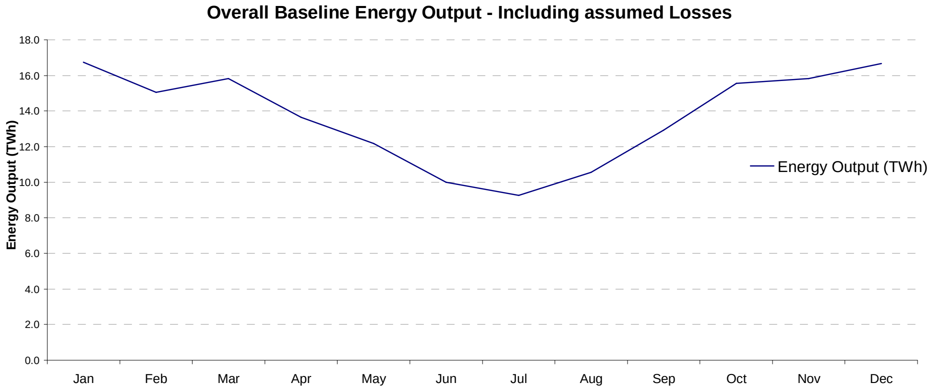


Figure 5-24: UK overall monthly baseline energy output – including assumed losses

The overall modelled capacity factor value of 39.2% (including assumed losses) is significantly higher than historical average estimations reported in DUKES (2010) which average 27.6% (Table 5-5). However, the DUKES values do appear to be on the low side. This is a reflection of the technology's current early maturity and the challenges associated with the early stages of any new technology. However, the modelled value is almost identical to the value attained by Mott MacDonald (2010) for assessing projected costs of Offshore Wind.

UK Average Offshore Wind Historical Capacity Factors					
2005	2006	2007	2008	2009	Average
27.2	28.7	25.6	30.4	26.0	27.58

Table 5-5: Historical Average UK Offshore Wind Capacity Factors (DUKES 2010)

5.6 Climate Change Impact

This section investigates the projected wind speed intra-annual and annual average climate variability and its impact on the baseline offshore wind speed model (section 5.2.1) and on the UK potential offshore wind resource (section 5.3.3). As previously discussed, wind speed projections were not included in the UKCP09 probabilistic projections and the same approach to offshore wind has been used for onshore wind (Chapter 4). It uses wind speeds from HadRM3 to create wind climate change projections in a format similar to that of the UKCP09 probabilistic projections.

The main difference between the method used for onshore wind and offshore wind is that the climate projections are applied to a baseline wind speed model created directly from the same HadRM3 dataset for “current climate”.

5.6.1 UK Offshore Wind Speed Projections

Figure 5-25 shows the 2050s and 2080s wind speed percentage change from baseline for a medium emissions scenario at a 50% probability level. The projections show reductions in average annual wind speeds over most offshore locations for both future time periods. Much of the North Sea has a reduction of around 1% for the 2050s and 2% for the 2080s. Extreme south east locations show slight wind speed increases.

There appears to be a band of reduced wind speeds stretching from off the west coast of Shetland, through the west of Scotland, and extending through the east and west coastal waters of Ireland and continuing south west from the south west of Ireland. There are also large reductions in the extreme north east of Scotland, which is part of the same band, stretching from the south-east of Orkney down the coast to Moray Firth. The largest wind speed reductions are seen in the Irish Sea, which shows reductions of up to 5% for the 2050s and 7% for the 2080s. Extreme south west locations show an annual increase of wind speeds up to 1.5%. The 2080s projections have very similar characteristics to the 2050s but show additional wind speed reductions of up to 1%.

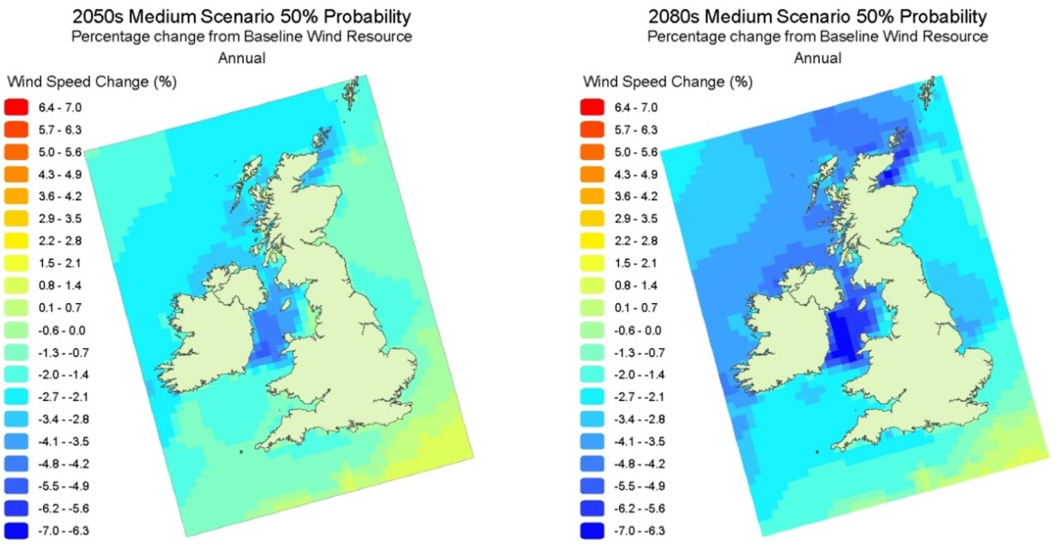


Figure 5-25: Projected annual wind speed change for the 2050s and 2080s medium scenario

Summer and winter months for the 2050s and 2080s are shown in Figure 5-26 and Figure 5-27. Summer months show greater reductions of wind speeds than winter months. Most offshore locations around the UK show reductions of around 3% for the 2050s and around 5% for the 2080s. The most extreme reductions are in the Irish Sea with around 7% for the 2050s and reaching 11% for the 2080s. There are slight increases east of Orkney of around 2-3% but these increases reduce in the 2080s.

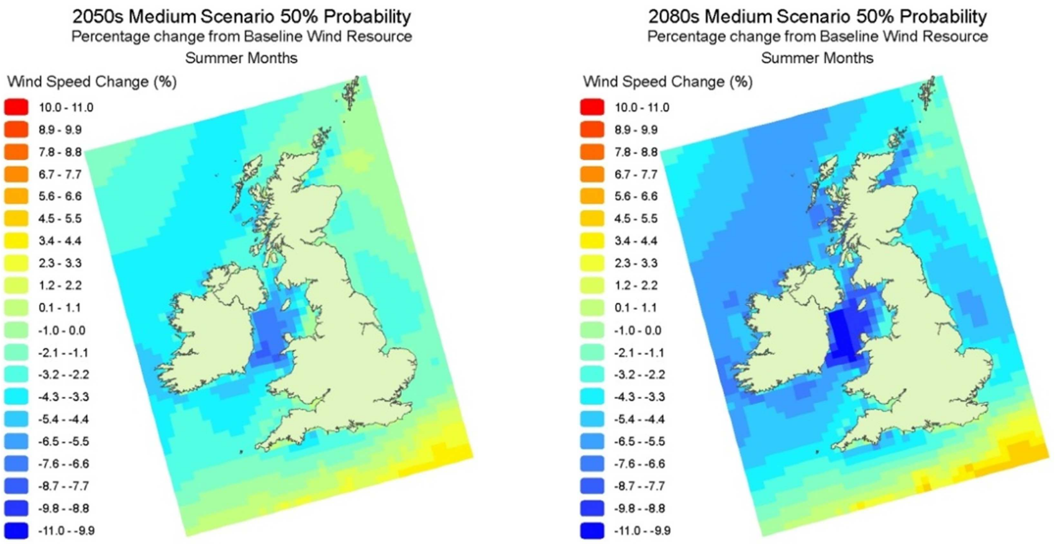


Figure 5-26: Projected Summer months wind speed change for the 2050s and 2080s medium scenario

In winter months, the 2050s show wind speed reductions of up to 4% in more northerly locations such as around and to the west of Orkney with the 2080s showing up to 7.2%

reductions. Travelling south the change reduces until half way down the UK on the east coast and just south of Ireland where slight increases begin. The wind speed increases are up to 2% in south easterly locations for the 2050s and 1% for the 2080s. The 2080s show similar wind speed change characteristics to the 2050s but the reductions are more pronounced, especially in the north around Orkney and down the west coast into the Irish Sea.

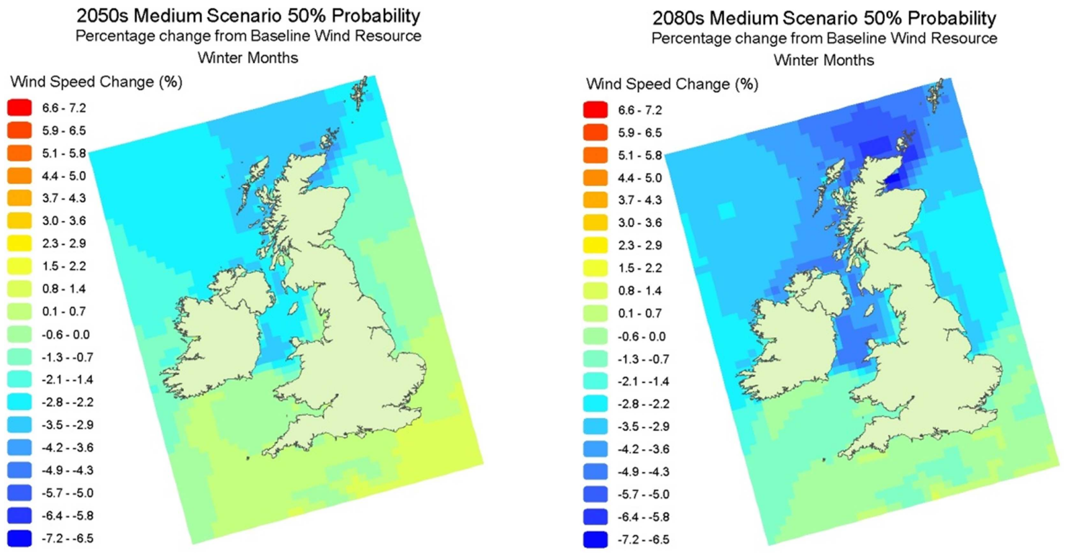


Figure 5-27: Projected Winter months wind speed change for the 2050s and 2080s medium scenario

Figure 5-28 and Figure 5-29 show the 10%, 50% and 90% probability distributions for the 2050s and 2080s annual wind speed percentage change. To give examples of probability levels at different locations there are 7 offshore wind farm locations labelled on the 50% of probability maps with the wind speed changes for those locations shown in Table 5-6. The spread between the 50% distribution level and the 10% and 90% levels are typically ±4.9% for the 2050s and ±5.3% for the 2080s.

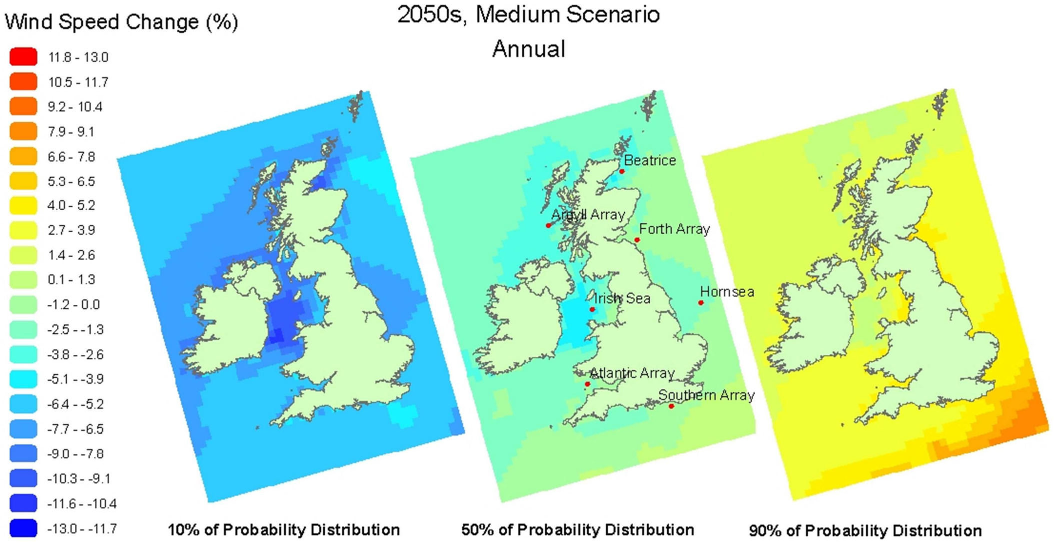


Figure 5-28: Projected annual wind speed change for the 2050s medium scenario with 10%, 50%, 90% probabilities

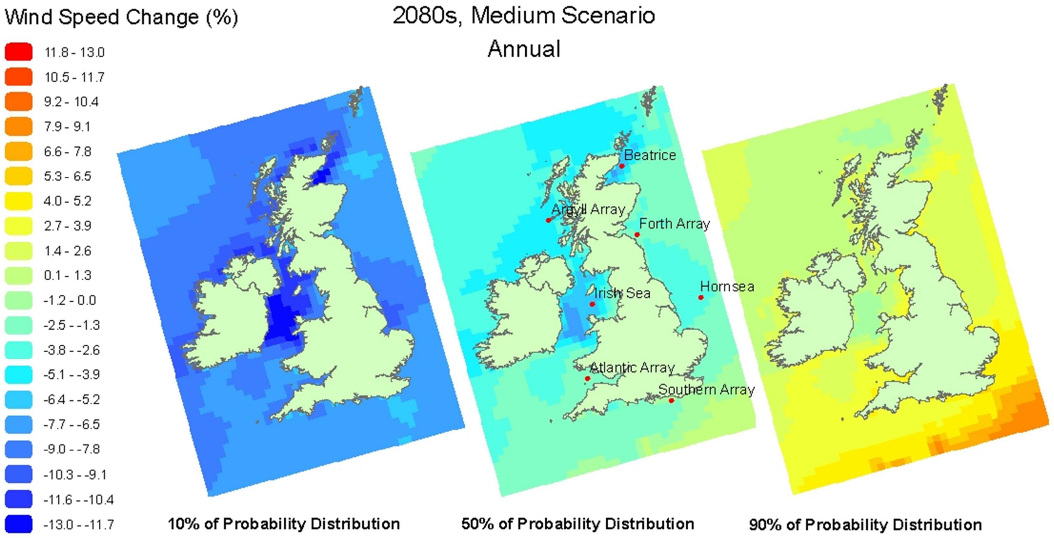


Figure 5-29: Projected annual wind speed change for the 2080s medium scenario with 10%, 50%, 90% probabilities

Location	Time Period					
	2050s			2080s		
	Probability Level (%)			Probability Level (%)		
	10	50	90	10	50	90
Beatrice	-8.0	-3.3	1.4	-10.7	-5.3	0.0
Argyll	-7.4	-3.2	1.1	-9.2	-4.5	0.2
Forth Array	-6.5	-1.2	4.1	-7.7	-2.6	2.6
Irish Sea	-9.3	-4.0	1.4	-11.6	-5.7	0.1
Hornsea	-6.9	-1.6	3.7	-8.8	-3.2	2.4
Atlantic Array	-5.9	-1.4	3.1	-7.4	-2.2	3.0
Southern Array	-5.5	-0.7	4.2	-6.8	-1.5	3.9

Table 5-6: Projected annual wind speed change for selected wind farm locations

5.6.2 UK Offshore Wind Energy Projections

The projected wind speed values for the 2050s and 2080s medium emissions scenarios at 10%, 50% and 90% values were processed in the same manner as for onshore wind to generate wind energy parameters for each of the future time periods.

5.6.2.1 Projected Capacity Factor Change

Figure 5-30 shows the 2050s and 2080s capacity factor annual change from baseline for a medium emissions scenario and a 50% probability distribution. The projections follow much the same characteristics as the wind projections showing slight reductions in capacity factor values except for the extreme south west which shows a very slight increase. The greatest reductions are in the Irish Sea where they are up to -2.7% for the 2050s and -3.7% for the 2080s. The majority of locations show reductions from -0.5% to -2.2% for the 2050s and from -1.0% and -2.5% for the 2080s.

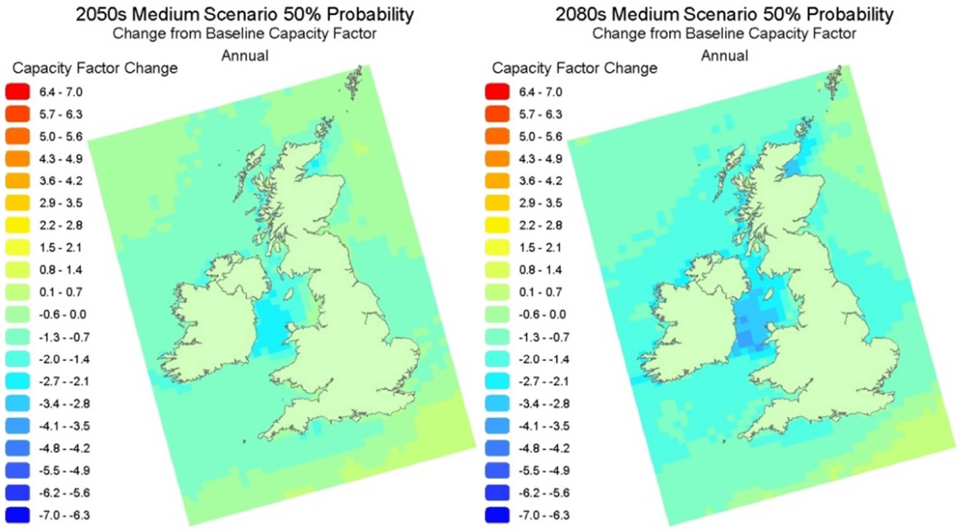


Figure 5-30: Projected 2050s and 2080s Annual Capacity Factor Change - Medium Scenario 50% Distribution

Figure 5-31 and Figure 5-32 show capacity factor change for summer and winter months. It is evident that capacity factor in winter months are less affected by the relative change in wind speeds when compared to summer months.

The lower baseline wind speeds in summer months result in a larger proportion of wind turbine time spent below rated capacity. In this case a slight reduction in wind speed can result in a larger reduction in capacity factor because of the cube power law. There will also be a higher proportion of time where the wind turbine is in its cut in state. In other seasons the turbine output would spend a larger proportion of time in the ‘at rating’ state and in this state a slight reduction in wind speed does not necessarily result in the wind turbine having a lower output as it could still be at its rated output after a wind speed reduction.

The greatest reductions in summer months are in the Irish Sea where they are up to -5.0% for the 2050s and -6.8% for the 2080s. The majority of locations show reductions from -0.8% to -3.0% for the 2050s and from -1.5% to -4.7% for the 2080s.

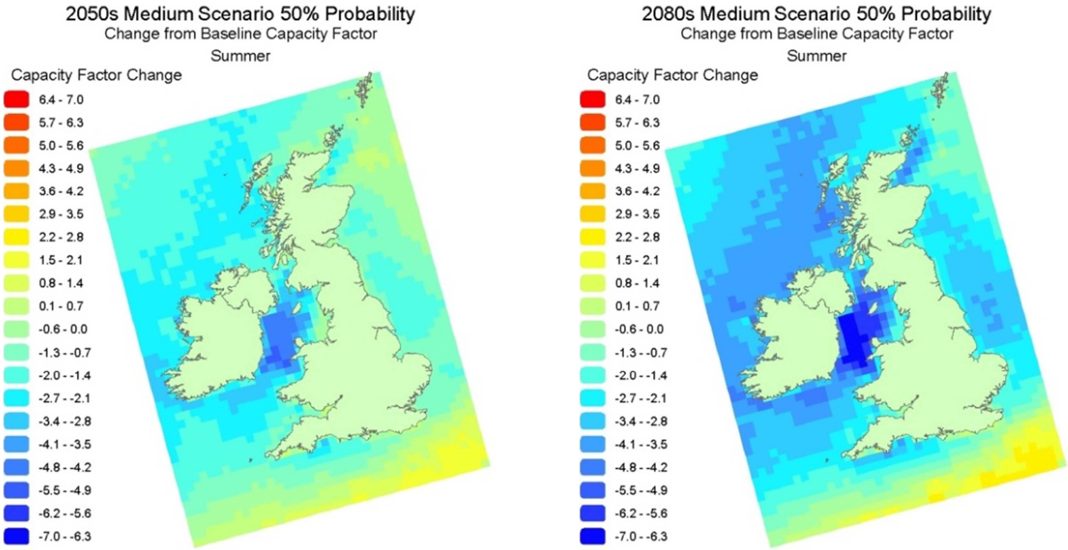


Figure 5-31: Projected 2050s and 2080s Summer Months Capacity Factor Change - Medium Scenario 50% Distribution

In winter months (Figure 5-32) the projected change in capacity factor is seen to be less than the relative change in wind speed and in some locations the capacity factor change characteristics are out of phase with the wind speed changes. Higher baseline wind speeds in winter months result in a relatively higher proportion of time above cut out and ‘at-rating’ states than other months and where, in these states, a reduction in projected wind speeds could actually result in no change in power output or even an increase due to less time in the above cut out state. Likewise, an increase in winter month wind speeds can result in lower capacity factors by increasing the proportion of time in the above cut out state. The 2050s and 2080s both show the majority of locations having winter capacity factor changes of -0.2% ±0.5%.

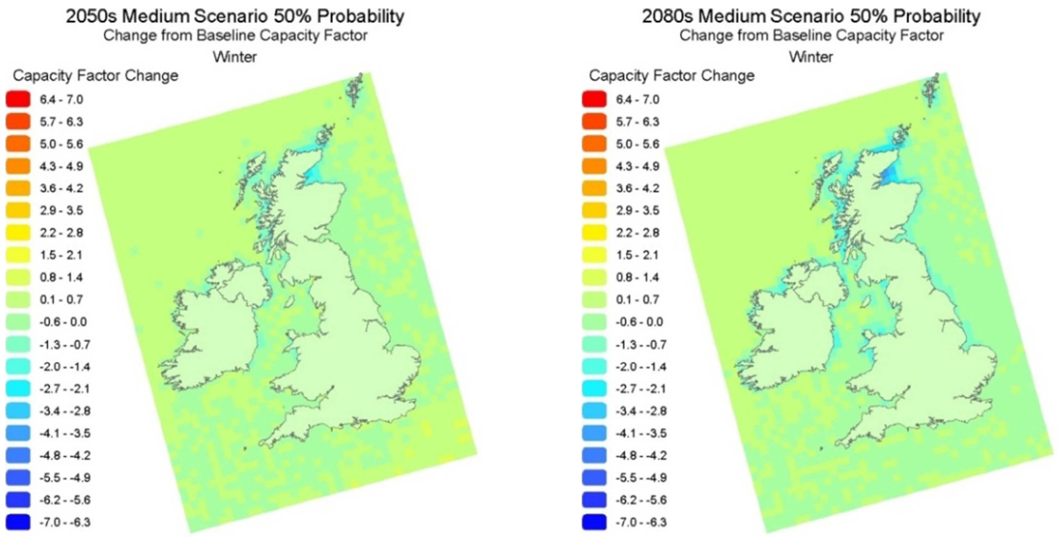


Figure 5-32: Projected 2050s and 2080s Winter Months Capacity Factor Change - Medium Scenario 50% Distribution

Figure 5-33 and Figure 5-34 shows the 10%, 50% and 90% probability distribution values for the 2050s and 2080s annual wind speed percentage change. Both show it is unlikely for the change in capacity factor to be more than ±4.5% from the 50% probability distribution projection values for the future time periods. As previously shown for wind (Figure 5-29), there are 7 offshore wind farm locations labelled on the 50% probability maps for both the 2050s and 2080s. The capacity factor projected changes for those locations are shown in Table 5-7.

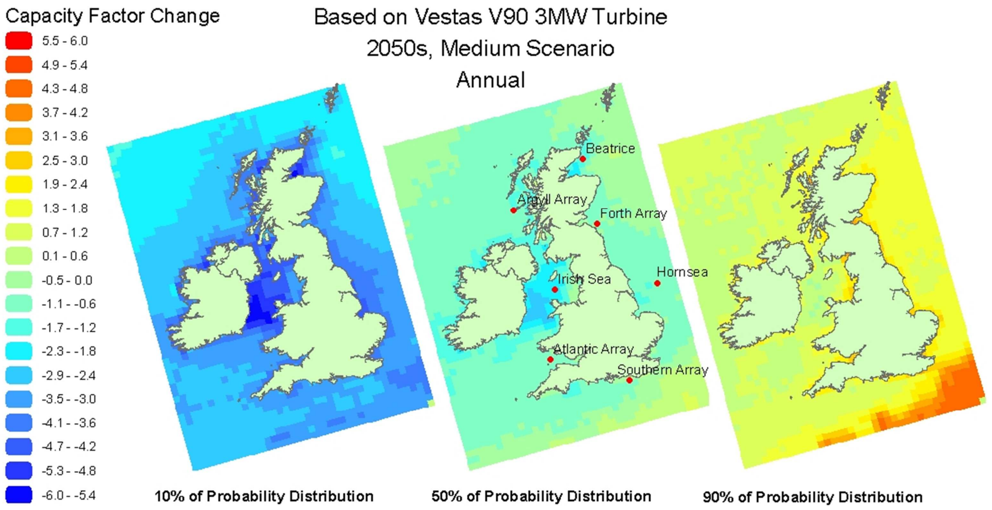


Figure 5-33: Projected annual capacity factor change for the 2050s and 2080s medium scenario with 10%, 50% and 90% probabilities

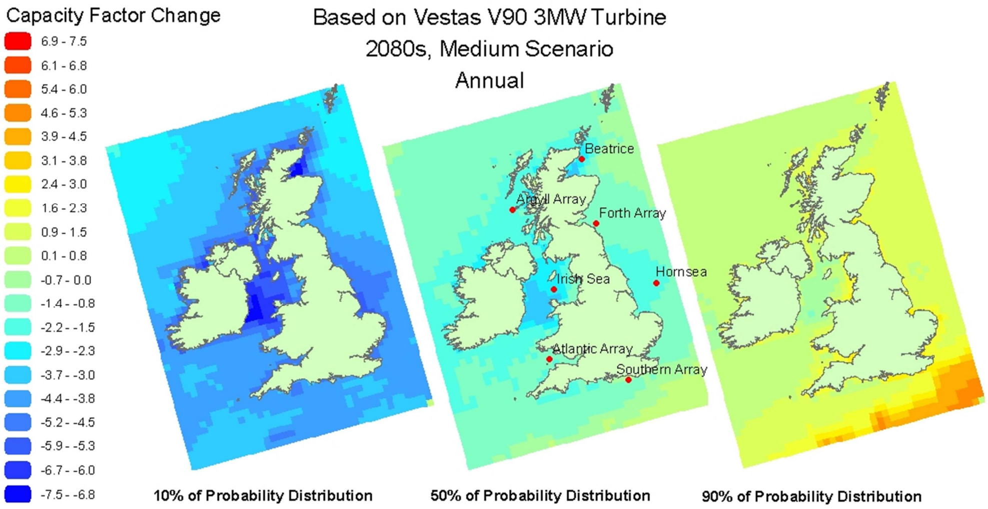


Figure 5-34: Projected annual capacity factor change for the 2050s and 2080s medium scenario with 10%, 50% and 90% probabilities

In Table 5-7 it can be seen that the spread between the 50% distribution level and the 10% and 90% levels are typically ±3.0% for the 2050s and ±3.4% for the 2080s.

Location	Time Period					
	2050s			2080s		
	Probability Level (%)			Probability Level (%)		
	10	50	90	10	50	90
Beatrice	-3.8	-1.2	1.1	-4.5	-2.2	0.6
Argyll	-3.3	-1.1	0.6	-4.2	-1.9	0.2
Forth Array	-3.5	-0.7	1.8	-4.1	-1.4	1.1
Irish Sea	-4.6	-2.0	0.4	-5.9	-2.8	0.0
Hornsea	-3.6	-1.0	1.2	-4.6	-1.7	0.9
Atlantic Array	-5.9	-1.4	3.1	-7.4	-2.2	3.0
Southern array	-5.5	-0.7	4.2	-6.8	-1.5	3.9

Table 5-7: Projected annual capacity factor change for selected wind farm locations

5.6.2.2 Projected Change of other Wind Turbine States

Figure 5-35 to Figure 5-39 highlight the projected change in different wind turbine operating states and clearly shows that the projected changes in offshore wind speeds have a resulting effect on the baseline offshore wind energy parameters.

Figure 5-35 and Figure 5-36 show the change in time spent at ‘above cut-out’ in winter and summer months. As would be expected it is the winter months where wind resource is higher that shows larger changes. There is a very clear divide between the north which shows reduced of time above cut-out and the south which shows increased time above cut-out in winter.

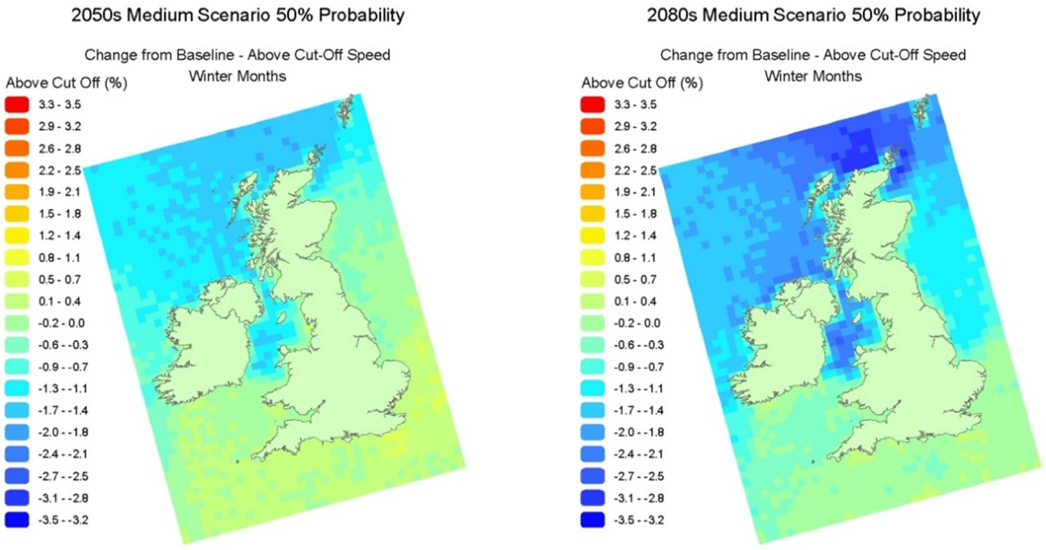


Figure 5-35: Projected change in percentage of time 'above cut off' state for 2050s and 2080s medium emissions in winter months

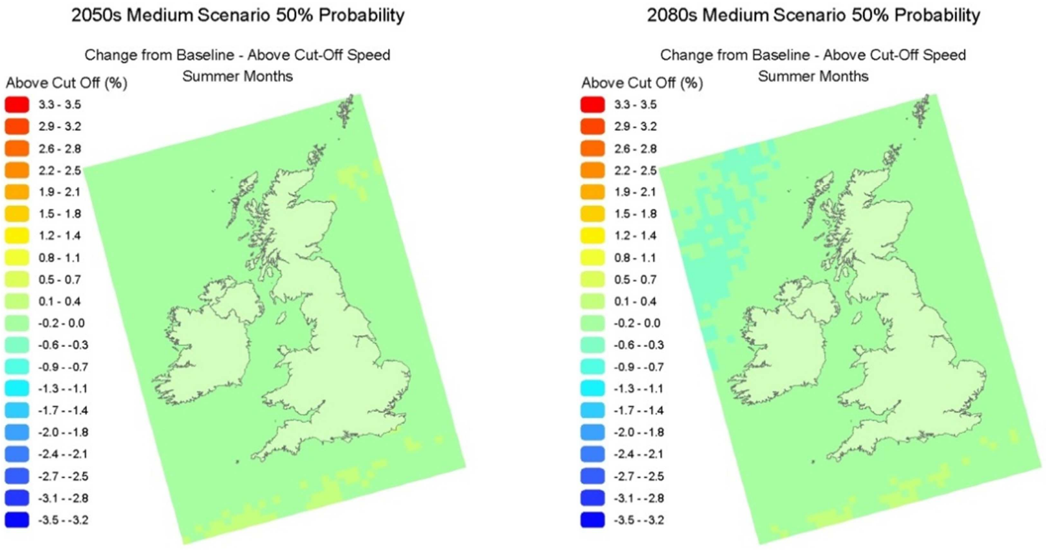


Figure 5-36: Projected change in percentage of time 'above cut off' state for 2050s and 2080s medium emissions in summer months

Figure 5-37 and Figure 5-38 show the change in time spent 'at rating' in winter and summer months. There appears to be a slight decrease in winter months but a very noticeable decrease in many areas in the summer months. This suggests that the wind speed reduction in summer months is causing an increase in the time the wind turbine is operating below its rated output.

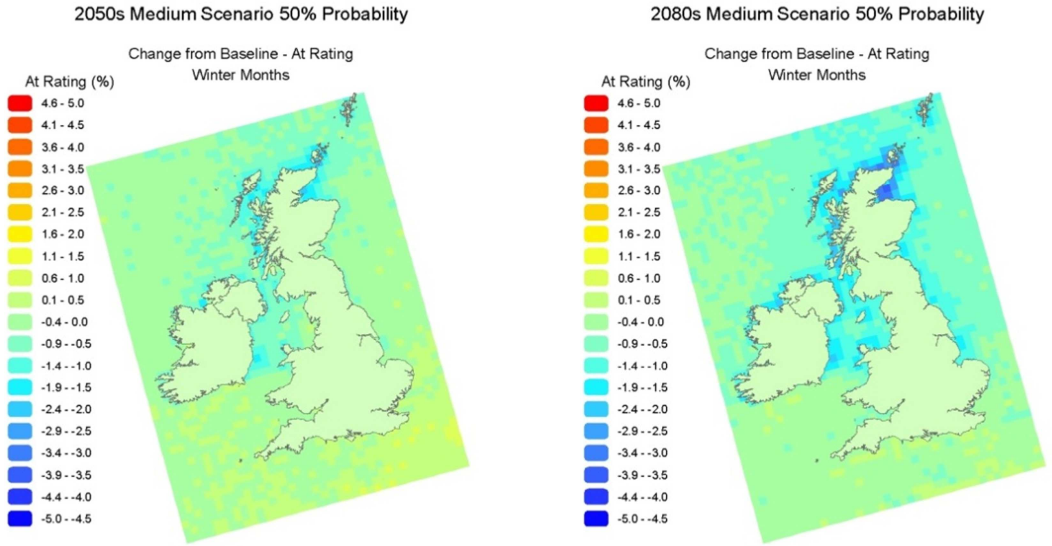


Figure 5-37: Projected change in percentage of time 'at rating' state for 2050s and 2080s medium emissions in winter months

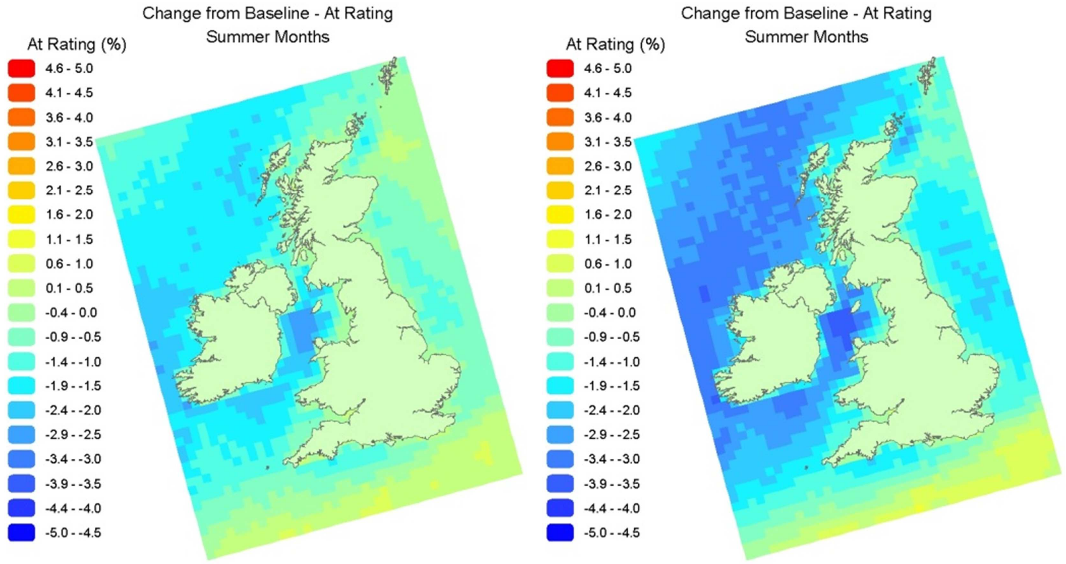


Figure 5-38: Projected change in percentage of time 'at rating' state for 2050s and 2080s medium emissions in summer months.

Figure 5-39 shows the annual change in time spent ‘generating’ and ‘below cut-in’ for the 2050s medium emissions. There appears to be an increase in the time the wind farm is operating in the far north and extreme south. The Bristol Channel area has quite a significant reduction in the annual time below cut-in.

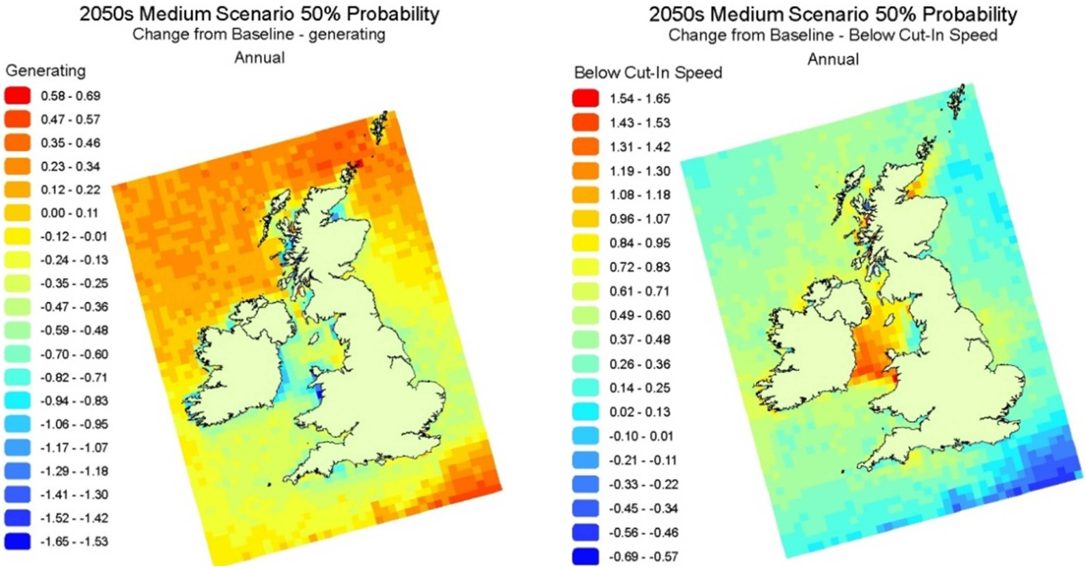


Figure 5-39: Projected annual change in percentage of time ‘generating’ (left) and ‘below cut-in’ (right) states for the 2050s medium scenario 50% probability

5.7 The Effect of Climate Change on Offshore Wind Resource

This section explores the changes that projected wind speeds will have on the UK offshore wind energy resource and yield discussed in the previous section. This is achieved by applying the projected change in capacity factor at each of the wind farm locations and weighting the energy output by the installed capacity at each wind farm.

The capacity factor changes for Rounds 1, 2 and 3 and Scottish exclusive wind farm locations are shown in Table C-5 to Table C-8 respectively for a 2050s medium emissions scenario with 50% probability. The values do not include loss assumptions discussed earlier. The parameters are changes from the values in Table C-1 to C-4 in Appendix C. As an example, the baseline annual capacity factor for Barrow is 42.7% (from Table C-1 in Appendix C), the projected annual capacity factor change for Barrow is -0.66% (from Table C-5 in Appendix C) giving a projected capacity factor of 42.1%.

Table 5-8 shows the weighted average capacity factor change values for all wind farm locations (Table C-5 to Table C-8 in Appendix C) for the 2050s and 2080s. The values assume losses. Values without losses are shown in Table-C9 in the Appendix.

Scenario	**Projected Aggregate Capacity Factor Change From Baseline (%) – Assuming Losses**												
	ANN	**JAN**	**FEB**	**MAR**	**APR**	**MAY**	**JUN**	**JUL**	**AUG**	**SEP**	**OCT**	**NOV**	**DEC**
Baseline	39.23	47.12	46.87	44.53	39.66	34.24	29.07	26.03	29.7	37.58	43.75	45.99	46.87
2050s 50%	-0.81	0.01	-0.39	-0.61	-0.74	-1.2	-0.07	-0.87	-3.08	-2.78	-0.57	0.39	0.18
2080s 50%	-1.33	-0.15	-0.5	-1.35	-1.32	-1.27	-0.83	-2.21	-4.67	-3.46	-0.33	0.28	-0.03
2050s 10%	-2.98	-0.56	-1.19	-1.98	-2.19	-3.83	-3.61	-5.82	-7.93	-5.59	-1.97	-0.61	-0.29
2050s 50%	-0.81	0.01	-0.39	-0.61	-0.74	-1.2	-0.07	-0.87	-3.08	-2.78	-0.57	0.39	0.18
2050s 90%	1.09	0.19	0.14	0.51	0.59	1.23	3.28	3.84	1.52	-0.27	0.61	1.02	0.38
2080s 10%	-3.76	-0.85	-1.42	-2.56	-3.66	-4.29	-4.81	-7.37	-9.65	-7.19	-1.93	-0.56	-0.66
2080s 50%	-1.33	-0.15	-0.5	-1.35	-1.32	-1.27	-0.83	-2.21	-4.67	-3.46	-0.33	0.28	-0.03
2080s 90%	0.85	0.15	0.11	-0.3	0.74	1.5	2.92	2.86	0.13	-0.16	1.01	0.87	0.33

Table 5-8: Projected Aggregate Capacity Factor Change from Baseline – assuming losses

Table 5-9 summarises the monthly and annual projected change from baseline for the 2050s and 2080s medium emissions scenario with 50% probability. As can be seen the 2050s shows a 2.1% reduction in generated electricity from wind energy, and the 2080s shows an even larger 3.4% reduction from baseline.

Scenario	Overall Baseline Energy Output – including losses (GWh)												
	ANN	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
Baseline (TWh)	164245	16752	15052	15832	13646	12172	10001	9255	10559	12930	15555	15825	16666
Projected Aggregate Change From Baseline Energy Output – including losses (GWh)													
2050s 50%	-3450	2	-127	-216	-254	-425	-23	-309	-1095	-958	-204	135	64
2080s 50%	-5557	-53	-160	-481	-456	-453	-287	-786	-1659	-1191	-117	98	-12
Percentage Change (%)													
2050s 50%	-2.1	0.0	-0.8	-1.4	-1.9	-3.5	-0.2	-3.3	-10.4	-7.4	-1.3	0.9	0.4
2080s 50%	-3.4	-0.3	-1.1	-3.0	-3.3	-3.7	-2.9	-8.5	-15.7	-9.2	-0.8	0.6	-0.1

Table 5-9: Projected Change from Aggregate Baseline Energy Output

Table 5-10 shows just the annual wind energy projection changes for a medium emissions scenario in 2050s and 2080s and includes the 10% and 90% distribution points as well as the 50% distribution midpoint.

Offshore Wind - Future Climate Energy Output			
Scenario	**Generated (GWh)**	**Change (GWh)**	**Change (%)**
Baseline	**164,245**		
2050s 10% Probability	151,774	-12,471	-7.59%
2050s 50% Probability	160,835	-3,410	-2.08%
2050s 90% Probability	168,822	4,577	2.79%
2080s 10% Probability	148,498	-15,747	-9.59%
2080s 50% Probability	158,687	-5,558	-3.38%
2080s 90% Probability	167,803	3,558	2.17%

Table 5-10: Annual Climate Change Values from Baseline Wind Energy Output

Figure 5-40 and Figure 5-41 show the baseline and the 10%, 50% and 90% probability monthly values for the 2050s and 2080s.

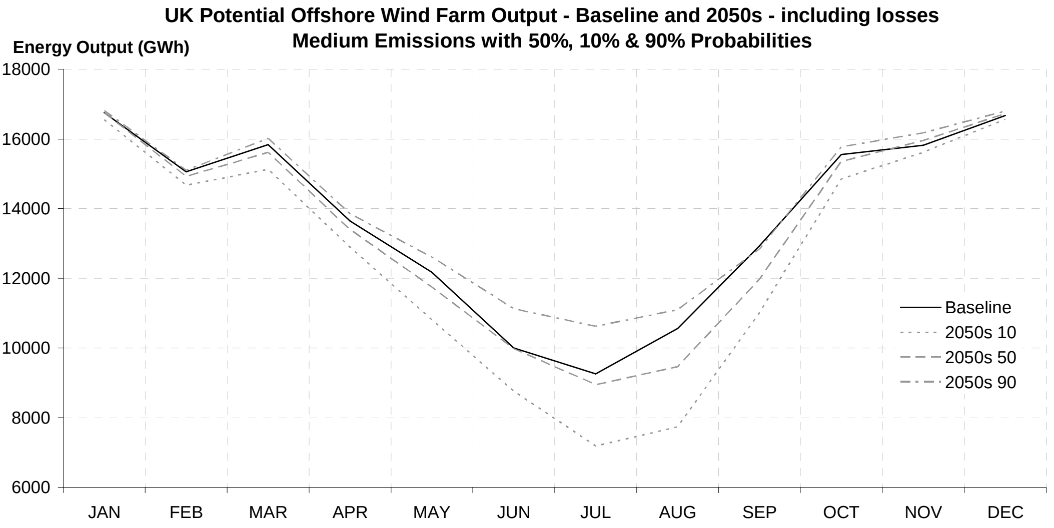


Figure 5-40: Potential Offshore Wind Farm Baseline Output and values for the 2050s medium emissions scenario at 10, 50% & 90% probability distribution

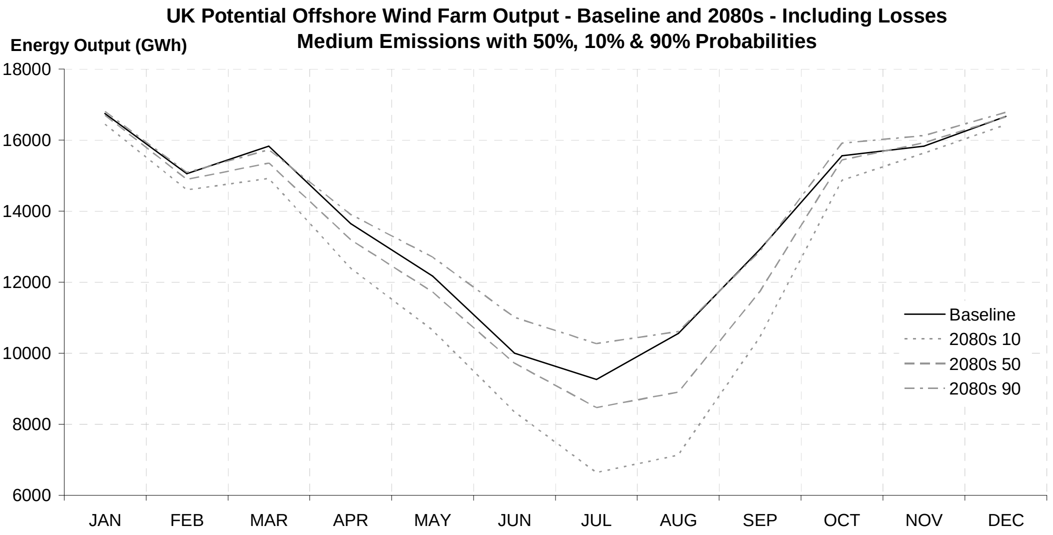


Figure 5-41: Potential Offshore Wind Farm Baseline Output and values for the 2050s medium emissions scenario at 10, 50% & 90% probability distribution

It is clear for both the 2050s and 2080s future time periods that there is an overall reduction from the baseline of potential offshore wind energy values. Summer months have the greatest reduction with winter months showing very little change and the 2050s actually show a slight increase in wind energy output.

5.8 Offshore Wind Summary

Accurate estimates of mean monthly offshore wind power resource have been generated from monthly wind speed data using HadRM3 wind speed data, a Rayleigh distribution and a generic wind turbine power curve. Baseline models of wind speed and wind energy output have been created and validated. Estimations of total UK offshore wind energy output have been created based on the locations and size of all operational and planned offshore wind turbine sites.

The offshore baseline wind model shows good agreement with the BERR Atlas wind speeds with an RMSE of 0.56 m/s and on average the HadRM3 wind speeds are only 0.08 m/s lower than the BERR Atlas value. It also shows good agreement when compared to observed wind speeds at several offshore wind farm locations; however the observations are very limited and averaged over a relatively small time period (approximately 3 years) compared to the model (30 years). The modelled average wind speed is approximately 0.5 m/s lower than the observations. Each observed average monthly wind speed is typically within ±10% of the modelled wind speed at any location. The offshore wind energy model was compared to a limited source of offshore wind farm observed capacity factors. The wind energy model typically reports values 6-8% higher than the observations. Similarly to the wind speed comparison the observations are over a small period of time and this comparison is of interest but of limited use as a validation method.

The 2050s appear to indicate negative changes in wind speed of typically -1.8% (-9.3% to 1.6%) and -3.0% (-8.1% to 2.0%) in the 2080s. The overall annual wind energy output from all offshore operational and potential wind turbine sites is estimated to be in the region of 164.245 TWh with the baseline climate. It is estimated that climate change could change this by -2.1% (-7.6% to 2.8%) for the 2050s and -1.4 (-6.7% to 3.5%) for the 2080s. The future offshore wind energy resource is more seasonally variable.

In summer months when resource is seasonally lower there is a significant reduction. July has an estimated change of -3.3% (-22.4% to 14.7%) for the 2050s and -8.5% (-28.3% to 11.0%). In comparison, January has a change of 0.0% (-1.2% to 0.4%) for the 2050s and -0.3% (-1.8% to 0.3%) for the 2080s.

The difference in the uncertainty between winter and summer months is related to the wind turbine power curve characteristics. In winter months the typical offshore wind turbine will spend a large amount of time in its at-rated output, in summer months the output of the turbine will be much more sensitive to wind speed variability as it will spend a large amount of time in the curve part of the power curve, below the rated value, where any slight change in wind will have a large effect on the power output due to the wind to power cube effect as discussed earlier.

Table 5-11 shows the offshore wind capacity factor values estimated in this chapter. These figures are used in chapters 7 and 8 when calculating offshore wind levelised cost values.

Technology	Climate Scenario						
	Baseline	2050 10%	2050 50%	2050 90%	2080 10%	2080 50%	2080 90%
Offshore Wind	35.1	33.2	35.0	36.6	32.8	34.6	36.4

Table 5-11: Offshore wind capacity factor values

6 Other Technologies

The main objective of this chapter is to discuss other technologies that are susceptible to resource variability due to climate change. Ideally, all other technologies justify as in depth an analysis as performed for solar, on- and offshore wind, in the previous chapters, but this is not possible due to limited time-scale and resource of this study. However, a reasonable assessment of wave energy and its sensitivity to climate change is performed. The other technologies are discussed in brief. Hydro has a very brief climate sensitivity analysis performed using data directly from Niall Duncan’s PhD study ‘Mapping Scotland's Hydropower Resource’ (Duncan 2012) in which he includes analysis of hydro intra-annual and annual average climate variability using UKCP09 climate input parameters.

The yellow blocks in the thesis flowchart (Figure 6-1) signify the areas of the thesis connected with this chapter.

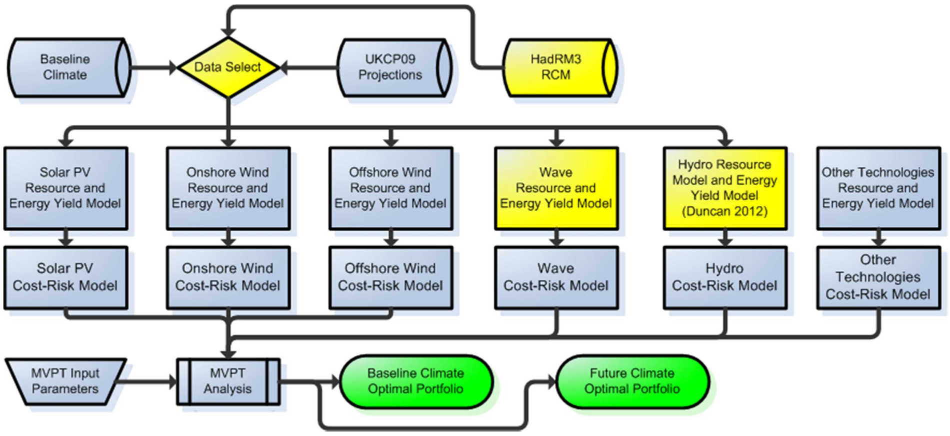


Figure 6-1: Thesis flowchart and wave and hydro resource blocks

6.1 Wave Power

6.1.1 Introduction

While it was hoped to perform an in depth wave resource analysis of all UK coastal waters, in a similar manner to the previous solar PV and Wind chapters. The effort of performing this was deemed to be out-with the available time-scale and resource of this study. Indeed it is a PhD in itself.

Ideally, the method would follow a similar approach as performed in previous chapters for solar PV and wind. It would involve running numerical wave energy models that are driven by output for the baseline climate and future climate scenarios for different greenhouse gas emission scenarios, then performing a comparative assessment. This described approach has been undertaken by Reeve *et al.* (2011) for the Wave Hub location with interesting results showing increases of wave power in the region of 2-3% for the A1B scenario (UKCIP09 medium scenario) using a GCM. However, the energy yield output from the WEC device was found to reduce by 2 to 3%. This was largely due to the technical limitations of the device in larger waves.

Another comprehensive study worth mentioning which assesses uncertainty in wave energy resource states that the annual average climate change is likely to be small when compared with natural climate variability (Mackay *et al.* 2010a, 2010b).

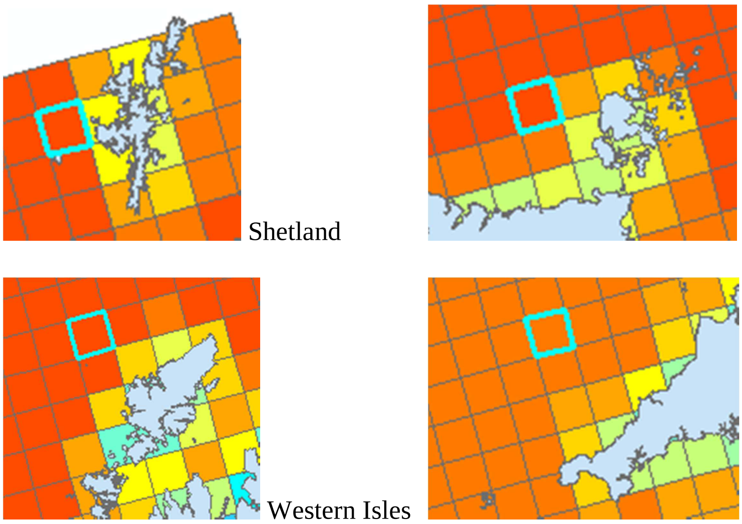
The chosen methodology for this study is a simpler approach using an established method, albeit with limitations. It follows a similar approach of Harrison *et al.* (2005) where average wind speeds at the location of interest are converted to a Rayleigh distribution in the same manner as in the earlier wind energy chapters, but at a height of 19.5m above sea level. The wind speed distribution is then applied to the Pierson Moskowitz (PM) spectrum (Pierson and Moskowitz 1964) which describes a fully developed sea, i.e. a sea that has had wind blowing over it for a sufficient length of time (6-18hours) and distance (200-600km) for a steady state sea condition to be reached. The output from the PM spectrum is then used as input to a wave to power output of a WEC device. Energy yield is estimated from the power output of the WEC device. Different sets of results for the location are compared for baseline and future emission scenario climate wind speeds.

This study extends the work by Harrison *et al.* (2005) which was based on a single annual average wind speed for one location in the Atlantic Ocean, by investigating the monthly characteristics of several locations of varying latitudes on the west of the UK.

6.1.1.1 Locations for Investigation

This study of the potential impact of climate change on wave resource focuses on four geographic locations that are very likely to be close to locations hosting a high proportion of the UK’s future wave energy installations. They are all situated in westerly waters that are open to the large wave resource of the Atlantic Ocean. The locations are: the west coast of Shetland, Orkney, The Western Isles, and north-west off Cornwall. Shetland, Orkney and The Western Isles locations have been awarded leases by the Crown Estate for Wave Power development (Crown estate 2010). The location in Cornwell is chosen because of Wave Hub, which is an offshore grid connected facility for the testing of wave energy devices situated

10 miles off the coast of Cornwall (Wave Hub 2011). The locations are shown in Figure 6-2 and on the HadRM3 25km grid.



Shetland

Orkney

Western Isles

Cornwall

Figure 6-2 Shetland, Orkney, Western Isles and Cornwall wave energy locations for study

6.1.2 Baseline Resource

The aim of the first part of the section is to create baseline wave energy resource for the four chosen locations by converting wind speed resource to wave resource by using the Pierson Moskowitz (PM) spectrum. Wind speed data from the HadRM3 data set was used as the basis of evaluation of the wave energy baseline resource. Other potential sources of baseline resource are: ERA-40 Reanalysis: Wind and Wave time series available (1957-2002) and the Atlas of UK Marine Renewable Energy: Wind and wave monthly averages available 2000-2007. The main reasons for using HadRM3 data for assessing the sensitivity of wave energy to climate change were that the HadRM3 wind speed data has already been processed for offshore wind and it includes future climate projections, whereas other sources do not. The main disadvantage of using wind data is that a wind to wave methodology is required to relate the wind speed data to wave resource.

6.1.2.1 Creation of the wave energy baseline model

The following section describes the creation of the wave energy baseline model. Four locations are first chosen, average monthly baseline wind speeds are converted to a Rayleigh distribution which is then converted to wave energy using the Pierson-Moskowitz method. The wave energy values are then used as input into the power curve of the Pelamis wave energy convertor.

Conversion method:

Baseline average wind speed values calculated from HadRM3 wind speed output are shown in Table 6-1 for the four chosen wave power locations.

Baseline average wind speed at 80m (m/s)				
	Shetland	Orkney	Hebrides	Cornwall
Annual	10.20	9.92	10.27	9.57
January	12.80	12.66	12.91	12.13
February	12.46	12.37	12.54	11.76
March	11.42	11.19	11.34	10.62
April	10.09	9.79	9.91	9.29
May	8.55	8.39	8.69	8.22
June	7.66	7.44	7.86	7.57
July	7.33	7.13	7.58	7.13
August	7.97	7.65	8.1	7.35
September	9.52	9.06	9.61	8.26
October	10.89	10.36	10.89	9.9
November	11.51	11.1	11.52	10.98
December	12.27	11.96	12.24	11.67

Table 6-1: Baseline average 80 metre height baseline wind speeds at four potential wave power locations

The average wind speed values were converted to a height of 19.5 metres (Table 6-2) which is the required height for the Pierson-Moskowitz method. The height conversion was performed using the log power law (Manwell *et al.* 2002).

Baseline average wind speed at 19.5m (m/s)				
	Shetland	Orkney	Hebrides	Cornwall
Annual	8.75	8.51	8.80	8.21
January	10.98	10.86	11.07	10.40
February	10.68	10.61	10.75	10.08
March	9.79	9.60	9.72	9.11
April	8.65	8.39	8.50	7.97
May	7.33	7.19	7.45	7.05
June	6.57	6.38	6.74	6.49
July	6.29	6.11	6.50	6.11
August	6.83	6.56	6.95	6.30
September	8.16	7.77	8.24	7.08
October	9.34	8.88	9.34	8.49
November	9.87	9.52	9.88	9.41
December	10.52	10.26	10.5	10.01

Table 6-2: Baseline average 19.5 metre height baseline wind speeds at four potential wave power locations

The wind speeds at 19.5 m were characterised using the Rayleigh probability density function then converted to wave energy using the Pierson Moskowitz spectrum:

The Pierson-Moskowitz (PM) frequency spectrum is one of the most representative methods for modelling a sea surface. It describes a fully developed sea state that has been produced only by wind which has been blowing over a very large area at a constant rate for a long enough period of time to reach steady state. There are more complex models that are more accurate but require more detailed information (Lehmann 2006). For the required purposes of investigating the sensitivity of wave energy to climate change, the PM spectrum was deemed to be suitable for this study.

The Pierson-Moskowitz (1964) sea state $S(\omega)$ available from wind is given by

$$S(\omega) = \alpha g^2 \omega^{-5} \exp\left[-\beta\left(\frac{g}{\omega U_{19.5}}\right)^4\right] \tag{6-1}$$

where g is the gravity constant, $U_{19.5}$ is the average wind speed at 19.5 m above sea level and α and β are given by:

$$\alpha = 4\pi^3\left(\frac{H_S}{g T_O{}^2}\right)^2 \tag{6-2}$$

and

$$\beta = 16\pi^3\left(\frac{U_{19.5}}{g T_O}\right)^4 \tag{6-3}$$

Estimations for these constants are α = 0.0081 and β =0.74 (Pierson and Moskowitz 1964).

The empirical relationship between significant wave height (Hs) and wave period (T_O) and mean wind speed at 19.5 metres above sea height ($U_{19.5}$) are given by Neumann and Pierson (1963) as:

$$H_S = \frac{0.21}{g} U_{19.5}^2 \tag{6-4}$$

and

$$T_O = 0.81\left(\frac{2\pi}{g}\right)U_{19.5} \tag{6-5}$$

where H_S is the significant wave height in metres (m) and T_O is the wave period in seconds (s).

Table 6-3 and Table 6-4 show the estimated baseline monthly average significant wave height and wave period at the chosen locations as calculated using the wind output from the wind Rayleigh distribution output.

Average monthly significant wave height (m)				
	Shetland	Orkney	Hebrides	Cornwall
Annual	2.33	2.21	2.35	2.05
January	3.54	3.46	3.6	3.18
February	3.36	3.31	3.4	3.00
March	2.83	2.71	2.78	2.44
April	2.20	2.08	2.13	1.87
May	1.58	1.53	1.64	1.46
June	1.27	1.20	1.34	1.24
July	1.16	1.1	1.24	1.10
August	1.38	1.27	1.42	1.17
September	1.96	1.78	2.00	1.48
October	2.57	2.33	2.57	2.12
November	2.87	2.67	2.87	2.61
December	3.25	3.1	3.24	2.95

Table 6-3: Baseline average monthly significant wave height at four potential wave power locations

Average monthly wave period (s)				
	Shetland	Orkney	Hebrides	Cornwall
Annual	5.71	5.56	5.74	5.36
January	7.16	7.08	7.22	6.79
February	6.97	6.92	7.02	6.59
March	6.4	6.26	6.35	5.94
April	5.65	5.48	5.54	5.2
May	4.78	4.7	4.86	4.6
June	4.28	4.17	4.4	4.24
July	4.1	3.99	4.24	3.99
August	4.46	4.28	4.53	4.11
September	5.33	5.07	5.38	4.63
October	6.1	5.8	6.1	5.54
November	6.45	6.21	6.45	6.14
December	6.86	6.69	6.85	6.53

Table 6-4: Baseline average monthly wave period height at four potential wave power locations

For each chosen location the wave energy distribution output from the Pierson-Moskowitz conversion was applied to a generic power curve based on the Pelamis wave energy converter power curve (Table 6-5).

	To (S)																
Hs (m)	5	5.5	6	6.5	7	7.5	8	8.5	9	9.5	10	10.5	11	11.5	12	12.5	13
0.5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	0	22	29	34	37	38	38	37	35	32	29	26	23	21	0	0	0
1.5	32	50	65	76	83	86	86	83	78	72	65	59	53	47	42	37	33
2	57	88	115	136	148	153	152	147	138	127	116	104	93	83	74	66	59
2.5	89	138	180	212	231	238	238	230	216	199	181	163	146	130	116	103	92
3	129	198	260	305	332	340	332	315	292	266	240	219	210	188	167	149	132
3.5	-	270	354	415	438	440	424	404	377	362	326	292	260	230	215	202	180
4	-	-	462	502	540	546	530	499	475	429	384	366	339	301	267	237	213
4.5	-	-	544	635	642	648	628	590	562	528	473	432	382	356	338	300	266
5	-	-	-	739	726	731	707	687	670	607	557	521	472	417	369	348	328
5.5	-	-	-	750	750	750	750	750	737	667	658	586	530	496	446	395	355
6	-	-	-	-	750	750	750	750	750	750	711	633	619	558	512	470	415
6.5	-	-	-	-	750	750	750	750	750	750	750	743	658	621	579	512	481
7	-	-	-	-	-	750	750	750	750	750	750	750	750	676	613	584	525
7.5	-	-	-	-	-	-	750	750	750	750	750	750	750	750	686	622	593
8	-	-	-	-	-	-	-	750	750	750	750	750	750	750	750	690	625
8.5	-	-	-	-	-	-	-	-	-	-	750	750	750	750	750	750	750
9	-	-	-	-	-	-	-	-	-	-	-	-	750	750	750	750	750
9.5	-	-	-	-	-	-	-	-	-	-	-	-	-	-	750	750	750
10	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	750
10.5	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
11	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-

Table 6-5: Pelamis Power Matrix (kW output). Source: Pelamis (2008)

Monthly average baseline capacity factors were calculated (Table 6-6) based on the proportion of time in each output state in the Pelamis power matrix. As can be seen the level of resource is seasonal, with almost twice the amount of energy generated in winter months than in summer months. All locations have reasonably similar outputs. The more southerly Cornwall location has as slightly reduced output. The overall averaged annual capacity factor is 24.9%.

	Shetland	Orkney	Hebrides	Cornwall	Overall
Annual	25.5	24.6	25.8	23.7	24.9
January	30.9	30.9	30.9	30.8	30.9
February	30.9	30.9	30.9	30.5	30.8
March	30.2	29.9	30.1	28.8	29.7
April	27.4	26.6	26.9	24.8	26.4
May	21.3	20.5	22	19.6	20.9
June	16.4	15.1	17.6	15.9	16.2
July	14.4	13.2	15.9	13.2	14.2
August	18.2	16.4	19	14.5	17.0
September	25.6	23.7	25.9	19.8	23.8
October	29.4	28.2	29.3	26.9	28.5
November	30.3	29.7	30.3	29.5	30.0
December	30.8	30.7	30.9	30.4	30.7

Table 6-6: Baseline average monthly capacity factor (%) based on Pelamis Power Matrix

Other modelled wave energy converter parameters:

There are levels of wave resource that are too low or high for a wave energy convertor to operate. In a similar manner to wind power, wave devices have to shut down or limit production when resource is too high in order to protect the device. On the Pelamis power matrix (Table 6-5) the areas that are highlighted red are when the device is operating at full capacity. Table 6-7 shows the percentage of time below operational state. There appears to be a substantial amount of time at all locations throughout the year (typically around 46% annually) where the wave resource is too low to operate. In winter months there is significantly less time in the below operational state (typically 30-35%) than in summer months (typically 60-65%).

Average Baseline Proportion of Time Below Operational State (%)				
	Shetland	Orkney	Hebrides	Cornwall
Annual	44.9	46.7	44.3	48.9
January	29.9	30.4	29.4	32.6
February	31.3	31.6	30.9	34.4
March	36.0	37.2	36.4	40.3
April	43.6	45.5	44.7	49.0
May	54.9	56.2	53.7	57.7
June	62.9	65.0	61.0	63.8
July	66.2	68.2	63.7	68.1
August	60.0	63.0	58.8	65.9
September	47.4	50.8	46.7	57.4
October	38.7	41.9	38.8	44.7
November	35.5	37.6	35.5	38.3
December	32.0	33.4	32.2	34.8

Table 6-7: Average baseline proportion of time below operating state

Table 6-8 shows the percentage of time in operational state. Annually this appears to be in the region of 45% and varies roughly between 31% and 49% for summer and winter months respectively.

Average Baseline Proportion of Time in Operational State (%)				
	Shetland	Orkney	Hebrides	Cornwall
Annual	44.9	44.0	45.3	43.3
January	48.6	48.8	48.5	49.3
February	49.0	49.1	49.0	49.5
March	49.5	49.5	49.5	49.0
April	48.0	47.3	47.6	45.6
May	41.9	41.0	42.7	39.9
June	35.7	33.9	37.3	35.0
July	32.9	31.1	35.1	31.2
August	38.1	35.7	39.1	33.1
September	46.4	44.5	46.7	40.1
October	49.3	48.6	49.3	47.6
November	49.5	49.4	49.6	49.4
December	49.2	49.4	49.2	49.5

Table 6-8: Average baseline proportion of time in operating state

Table 6-9 shows the percentage of time in operational state and at full rating. Annually this appears to be in the region of 10% and varies roughly between 4% and 14% for summer and winter months respectively.

Average Baseline Proportion of Time Operational and at Full Rating (%)				
	Shetland	Orkney	Hebrides	Cornwall
Annual	10.0	9.5	10.1	8.8
January	14.2	14.2	14.3	13.7
February	14.0	13.9	14.1	13.4
March	13	12.6	12.9	11.7
April	10.6	10.0	10.3	8.8
May	6.8	6.3	7.2	5.8
June	4.3	3.7	4.8	4.0
July	3.4	2.9	4.1	2.9
August	5.1	4.3	5.5	3.5
September	9.4	8.2	9.6	5.9
October	12.2	11.2	12.2	10.2
November	13.1	12.5	13.1	12.3
December	13.8	13.6	13.9	13.2

Table 6-9: Average baseline proportion of time at full rating

Table 6-10 shows the percentage of time above operational state. This is where the WEC is not capable of shedding the excess wave power and shuts down. Annually this is in the region of 9% and varies roughly between 1% and 20% for summer and winter months respectively.

Average baseline proportion of time above rating (%)				
	Shetland	Orkney	Hebrides	Cornwall
Annual	10.3	9.2	10.4	7.8
January	21.5	20.8	22.1	18
February	19.7	19.2	20.1	16.2
March	14.5	13.4	14.1	10.7
April	8.4	7.2	7.7	5.4
May	3.2	2.8	3.6	2.4
June	1.4	1.1	1.7	1.2
July	0.9	0.7	1.2	0.7
August	1.9	1.3	2.2	0.9
September	6.2	4.7	6.5	2.5
October	12	9.6	12	7.7
November	15	13	15	12.4
December	18.8	17.2	18.6	15.7

Table 6-10: Average baseline proportion of time above operational state

To show the time spent in different states more clearly, Figure 6-3 is the baseline proportion of time the wave energy device is in different states for the Shetland location.

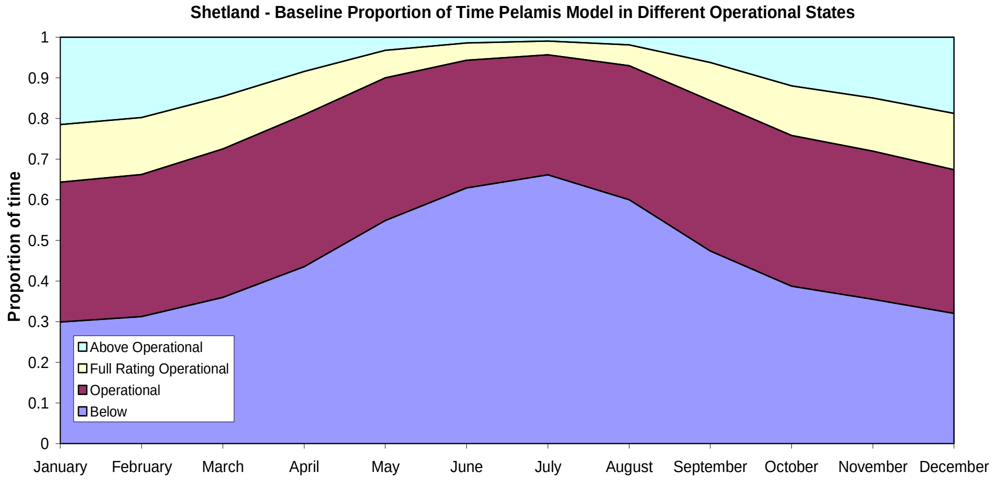


Figure 6-3: Baseline proportion of time in different operating states for Shetland location

6.1.3 Validation

The Atlas of UK Marine Renewable Energy Resources (BERR 2008a) includes wind and wave resource estimations. As a method of validating both the HadRM3 wind resource at each wave location as well as the estimated wave resource by conversion using Pierson-Moskowitz, the wind and wave data from both data sets are compared. The validation is limited to H_s as T_e is not available in the BERR marine atlas.

Figure 6-4 shows comparisons of HadRM3 wind speeds with UK Marine Atlas (BERR 2008a) wind speeds for the Shetland locations. The other three locations are shown in Figures D-1 to D-3 in Appendix D. The two sources of wind speed estimations are very similar with root mean square errors of 0.28, 0.49, 0.68 and 0.44 m/s respectively for the four locations.

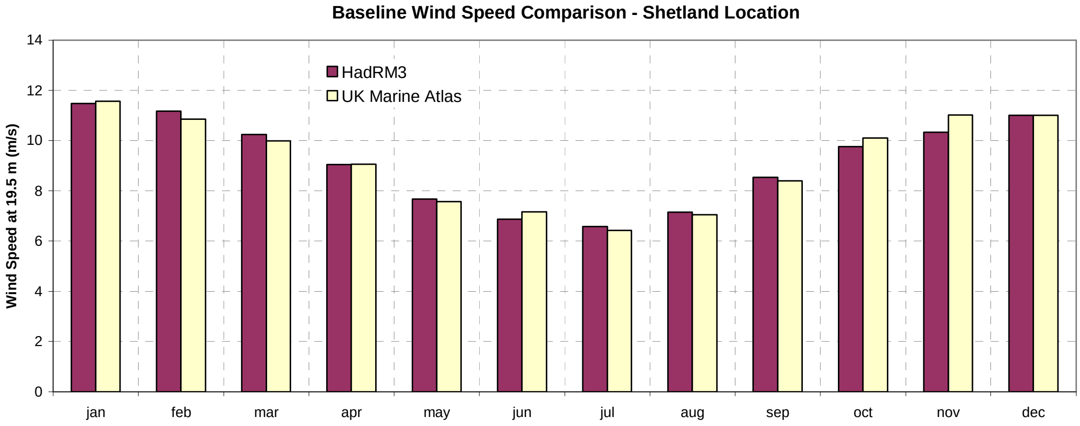


Figure 6-4: Comparing Wind speed data for Shetland Location

Table 6-11 shows the significant wave heights for the Shetland locations from three different sources: BERR actual, converted from BERR wind speed, converted from HadRM3. The other three locations are shown in Tables D-1 to D-3 in Appendix D. The RMSE values between BERR actual and from HadRM3 are 0.33m, 0.36m, 0.4m and 0.24m respectively for the locations. RMSE values between BERR from wind speed and HadRM3 from wind speed are 0.14m, 0.25m, 0.34m, 0.21m respectively for the four locations. The figures suggest that the wave height estimations using the PM method are on the low side. The effect could be significant due to the squaring effect of the H_S to power relationship, but the extent would depend on the resource at any specific location: a location with high wave resource may see negligible change if a large proportion of time is in the 'at rated' state, whereas, a location with a lower resource which spends a large amount of time in 'below rated' state may be subject to substantial variability. A brief look back at Table 6-5 suggests an error of 0.25m in H_S could result in power output error of up to 5%.

Significant Wave Height (m)			
	BERR actual	BERR from wind speed	HadRM3 from wind speed
Annual	2.61	2.35	2.33
January	3.64	3.59	3.54
February	3.36	3.17	3.36
March	2.96	2.69	2.83
April	2.58	2.21	2.2
May	2.06	1.54	1.58
June	1.78	1.38	1.27
July	1.49	1.11	1.16
August	1.69	1.34	1.38
September	2.35	1.9	1.96
October	2.81	2.75	2.57
November	3.39	3.27	2.87
December	3.4	3.25	3.25

Table 6-11: Shetland location significant wave height (*Hs*) comparison

There are a number of uncertainties in the estimation of wave energy output from the four locations:

HadRM3 wind speed data uncertainties and uncertainties from the use of the Rayleigh distribution have been discussed previously in section 5.2.2.1. There are also uncertainties between the HadRM3 and the BERR wind speed data, the sources of the uncertainties include the difference in grid resolution and shape and the number of years the average wind speeds are bases on. HadRM3 is based on 30 years of RCM data between 1961 and 1990, whereas BERR data is based on 7 years of data from the Met Office Weather Prediction System (NWP) between 2000 and 2007.

It has previously been mentioned that the PM spectrum assumes a fully developed-wind created sea state, one other assumption is that it assumes infinite depth of the ocean and this may result in further uncertainty as the locations of interest are in relatively shallow waters (60-90m). The PM spectrum is also empirically derived and originally derived from measurements of sea states in the North Sea (Pierson and Moskowitz 1964) and there will be additional uncertainty introduced by using the empirical at a location with different localised characteristics.

The wind created sea does not fully include swell waves, hence the PM method will tend to under-estimate larger waves and production levels.

There is a large uncertainty associated with the WEC device. The one used in this analysis is based on the Pelamis prototype and will almost certainly have very different characteristics to other WEC devices and from the production version.

6.1.4 Climate Change Impact

The aim of this section is to investigate the potential wave energy resource intra-annual and annual average climate change and its impact on the baseline capacity factor values of the Pelamis wave energy converter as.

Figure 6-5 shows the projected monthly wind speed changes for the 2050s and 2080s medium scenarios with 10%, 50% and 90% projections at the Shetland location. The other locations are shown in Figures D-4 to D-7 in Appendix D. All show similar characteristics with wind in all seasons likely to reduce in average monthly wind speed. As mentioned earlier, the use of local winds with the PM spectrum means that the wave changes implicitly assume the local changes are similar to changes in the wider Atlantic Ocean.

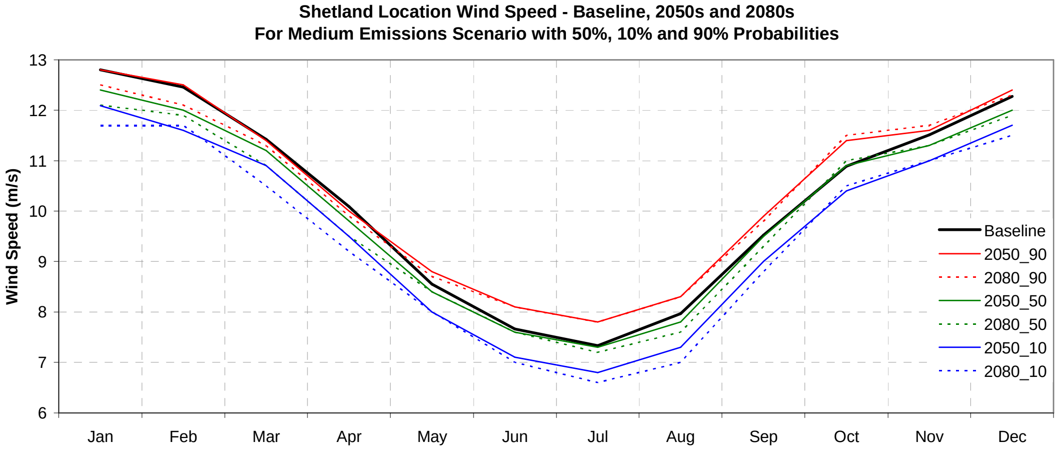


Figure 6-5: Shetland location - Projected Wind Speed change from baseline

6.1.4.1 Projected Capacity Factor change at locations

The projected change in capacity factor follows similar characteristics to the projected wind speeds, but the reductions are more amplified in summer months than in winter months. Winter months have a higher proportion where a wave devices time spent in the ‘full rating’ or ‘above operating’ states. A reduction in wave energy may actually increase generated energy by reducing the amount of time when there is too much wave energy to operate. This is apparent in Figure 6-6 to Figure 6-9.

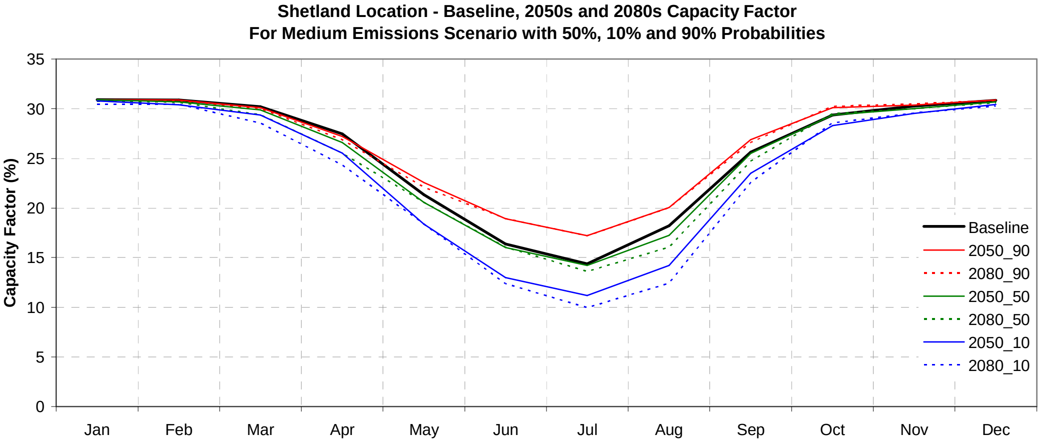


Figure 6-6: Shetland location – projected Capacity Factor change from baseline

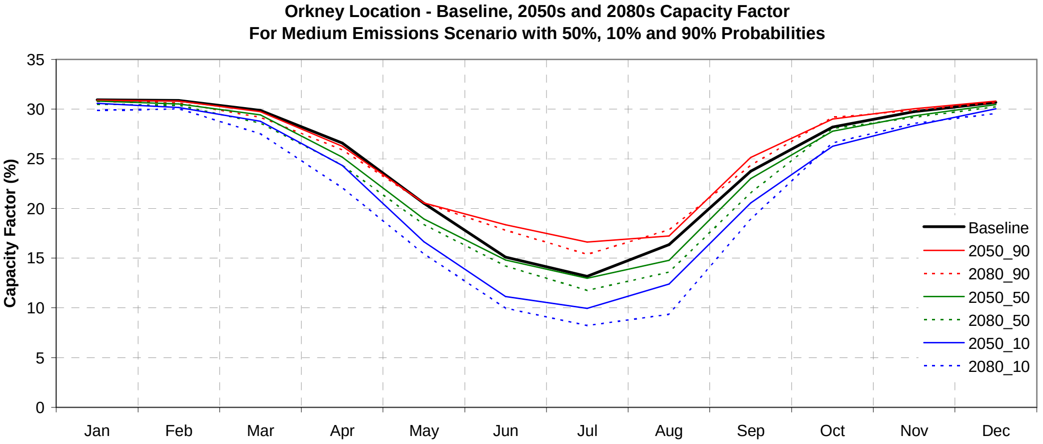


Figure 6-7: Orkney location – projected Capacity Factor change from baseline

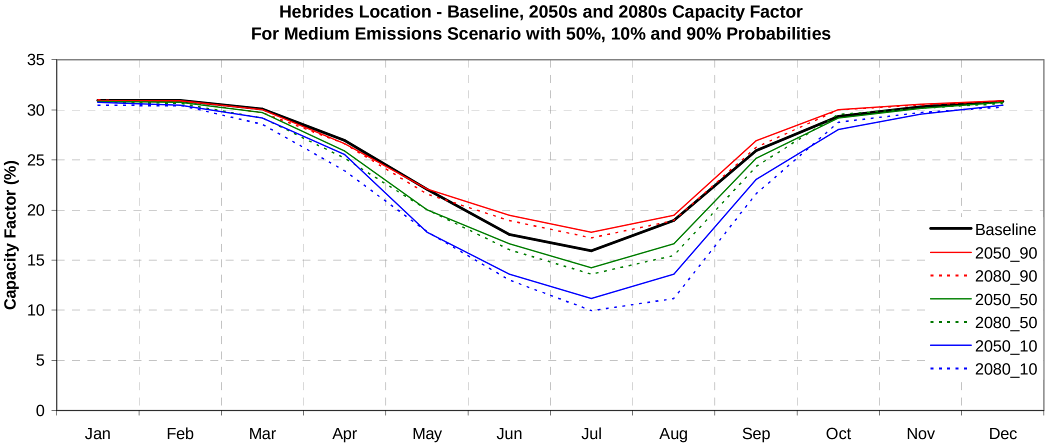


Figure 6-8: Hebrides location – projected Capacity Factor change from baseline

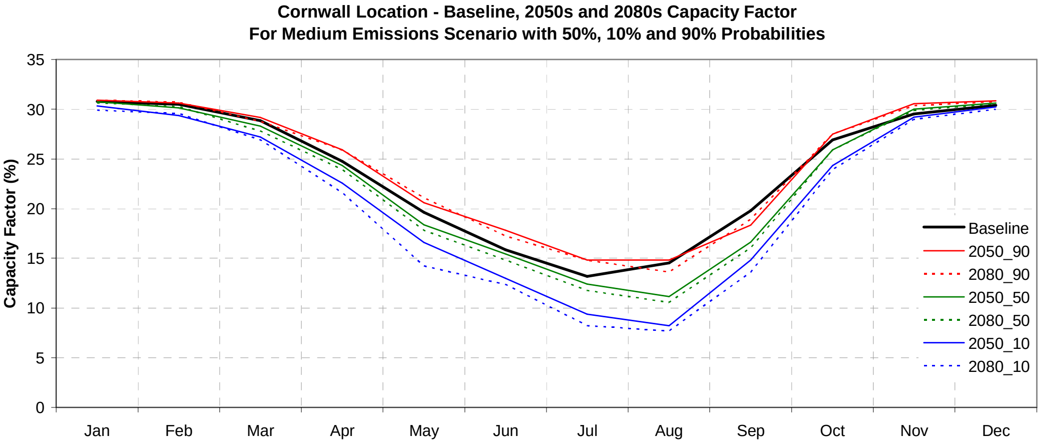


Figure 6-9: Cornwall location – projected Capacity Factor change from baseline

Table 6-12 shows there is quite a significant projected reduction in capacity factor for 2050s and 2080s medium scenario. Overall annual capacity factor reductions of -0.67 and -1.09% are projected for the 2050s and 2080s timescales for the medium emissions scenario with a 50% probability level. Table 6-13 shows the same but with the numbers expressed in percentage change of capacity factor from baseline.

Projected annual percentage point change in CF from baseline						
Time Period	2050s			2080s		
Probability Level (%)	10	**50**	90	10	**50**	90
Shetland	-1.77	-0.35	0.86	-2.32	-0.69	0.76
Orkney	-2.22	-0.64	0.81	-3.30	-1.25	0.53
Hebrides	-2.21	-0.82	0.49	-2.84	-1.18	0.22
Cornwall	-2.46	-0.89	0.60	-3.15	-1.23	0.49

Table 6-12: Projected annual percentage point change in CF

Projected annual proportional change of CF from baseline (%)						
Time Period	2050s			2080s		
Probability Level (%)	10	**50**	90	10	**50**	90
Shetland	-6.95	-1.36	3.38	-9.12	-2.73	2.99
Orkney	-8.99	-2.59	3.29	-13.4	-5.07	2.16
Hebrides	-8.57	-3.18	1.91	-11.01	-4.59	0.84
Cornwall	-10.35	-3.75	2.52	-13.26	-5.19	2.07

Table 6-13: Projected annual change of capacity factor for selected wave locations

Figure 6-10 shows wave energy output percentage change for the 2080s and shows clearly the large climate sensitivity of the resource in summer months.

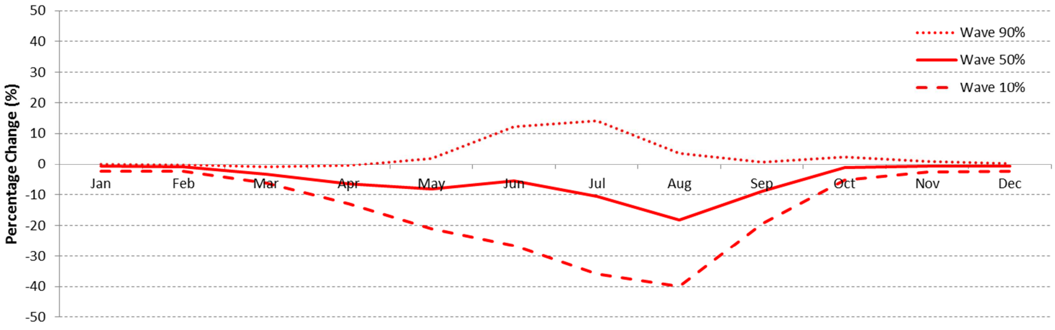


Figure 6-10: Wave energy output percentage change from the baseline climate to the 2080s medium emissions for 50% (10%, 90%) probability levels

6.1.5 Summary

Estimations of wave energy resource at four different locations have been generated using average wind speed data, the Rayleigh distribution and the Pierson-Moskowitz (PM) frequency spectrum. The input wind speed data is sourced from the HadRM3 and has been found to be favorably comparable with BERR (2008a) wind speed data for the baseline period. The model is run for the baseline climate, the 2050s and 2080s medium emissions scenario climate. The future climate results are compared with the baseline climate.

The projected output of the WEC used in this study (based on the Pelamis device) will change by approximately -1.4% (-7.0% to 3.4%) in the far north to -3.8% (-10.4% to 2.5%) in the far south for the 2050s medium emissions climate and -2.7% (-9.2% to 3.0%) in the far north to -5.2% (-13.3% to 2.1%) in the far south for the 2080s medium emissions scenario. The resource will be more seasonably variable with winter months which typically have larger resource than summer months having a slight decrease in wave resource, typically -0.25% (-0.4 to 0.1) for the 2050s, and summer months having a substantial reduction which appears to increase towards more southerly locations.

The method, results and sensitivity of wave energy output relative to a changing wind climate compares well with analysis performed by Harrison *et al.* (2005), for example, the method used here gives an estimated capacity factor of 30% for a wind speed of 10 m/s whereas the method in Harrison *et al.* (2005) gives a capacity factor of 31%. *Hs* and *Te* and sensitivity of output to wind speed are also similarly comparable.

The results in this study show different results from Reeve *et al.* (2011) for the Wave Hub location which showed increases of wave power in the region of 2-3% for the medium emissions scenario, whereas this study shows a decrease in the region of 3-4%. Reeve, as discussed follows a different method using a wave model which is driven from a different source of climate change wind speed data, and such a large difference in results is not surprising when this is taken into account. They however use a single GCM and offer no probabilistic interpretation. Direct comparison is therefore not possible.

To fully investigate this it will require a full wind-wave model driven by multiple GCMs, preferably the set used to derive the 11 member RCM ensemble in UKCP09.

Table 6-14 shows the wave energy capacity factor values estimated in this chapter. These figures are referred to in chapter 7 when calculating wave energy levelised cost values.

Technology	Climate Scenario						
	Baseline	2050 10%	2050 50%	2050 90%	2080 10%	2080 50%	2080 90%
Wave	33.0	30.1	32.1	33.9	29.1	31.6	33.7

Table 6-14: Wave energy capacity factor values

6.2 Hydro

The hydro capacity factor figures used here are sourced from Duncan (2012) in his PhD thesis titled 'Mapping Scotland's Hydropower Resource'. The capacity factor figures shown in Table E-1 in Appendix E are from modelled hydropower plants in 5 catchment areas in Scotland. The resource for the baseline and future time periods have been estimated by modelling river flow in the catchment areas using observations for the baseline period (1961-1990) and output from UKCIP09 (2009) for the 2050s medium emissions scenario respectively. River flows are not a direct product for UKCP09 and they are evaluated by a sophisticated hydrological model. Climate change is simulated by comparing altered values of rainfall and evapotranspiration through the hydrological model. The probabilistic information is gained by using the UKCP09 weather generator to create a series of time series of rainfall and evapotranspiration. They are then run through the hydrological model to produce probability outputs of river flow. (Duncan 2012). 100 runs is the recommended minimum amount of runs to ensure statistically robust values (Jones *et al.* 2009). The ±2 standard deviation values from the 100 runs have been assumed to be the 10% and 90% confidence levels and the mean value has been assumed to be the 50% confidence level. Baseline and future river flows were modelled for each of the locations and used to drive hydro plant models with 100m of head (Duncan 2012). The average annual capacity factor values for each of the locations are shown in Table 6-15.

Location	Time Period			
	Baseline	2050s		
		10% probability	50% probability	90% probability
Oykel	65	57	63	70
Ewe	65	58	66	73
Cree	67	57	63	69
Irvine	68	57	63	69
Deveron	66	55	62	70
All	**66.1**	**56.7**	**63.4**	**70.2**

Table 6-15: Hydro plant annual average capacity factor values

Figure 6-11 shows the modelled capacity factor for each of the 5 locations. Each have similar seasonal characteristics, though it can be seen that Deveron appears to lag slightly (about 2 weeks) behind the others.

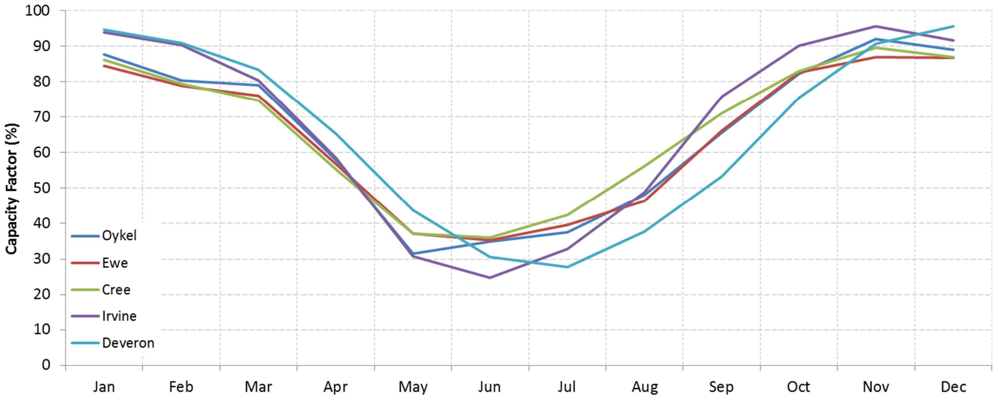


Figure 6-11: Hydro modelled baseline monthly capacity factor for selected locations

Figure 6-12 shows the baseline and 2050 medium emission scenario values for hydro capacity factor. The figures are based on the averaged values of all 5 locations. It indicates that hydro resource will increase in months November to February, reduce in the other months with largest reductions in the summer month, with an overall annual reduction. For the baseline climate the capacity factor ranges from 32% to 90%. There is a larger range for the 2050s of 27% to 92%.

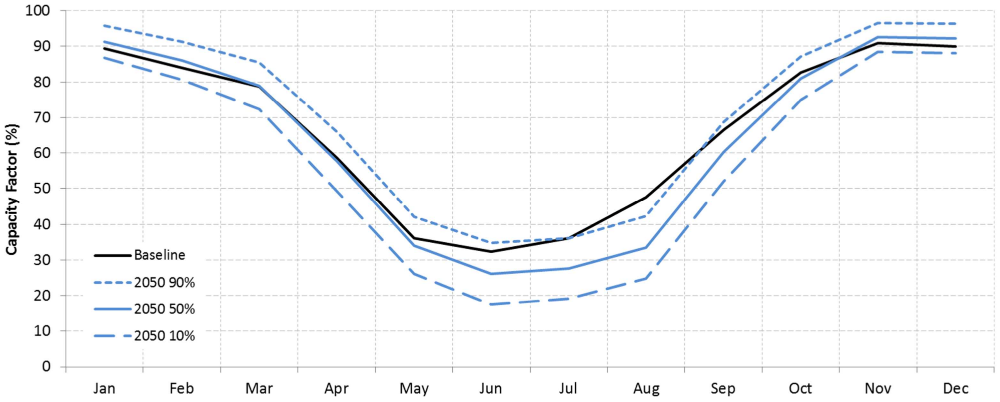


Figure 6-12: Hydro modelled baseline and 2050 medium emissions monthly capacity factor

Figure 6-13 shows the percentage change from the baseline climate and re-emphasis the uncertainty in summer months. August has a 90% probability of having a 10% reduction in hydro energy output.

Figure 6-13: Hydro energy output percentage change from the baseline climate to the 2050s medium emissions for 50% (10%, 90%) probability levels

6.2.1 Summary

The data from Duncan (2012) indicates slight increases in winter production for the 2050s medium scenario relative to the baseline climate, for example, a typical value of 2.4% (-2.2% to 7.2%) for December. However, in summer there are very significant reductions in production, for example -29.5% (-11.1% to 47.9%) for August. There is an overall annual change in production efficiency -4% (6.3% to -14.3%) in hydro efficiency projected for the 2050s medium emissions climate. The figures appear to mirror seasonal climate impact projections

The analysis performed here from the data from Duncan's 'Mapping Scotland's Hydropower Resource' (2012) is a very good indicator of how hydro will be affected by climate change. It is, however only covering modelled locations in Scotland and more southerly locations may well deviate from the results shown here. However, the results are still a good indicator of the overall sensitivity of hydro resource to climate change and of great value towards the objectives of this thesis.

Table 6-16 shows the hydro capacity factor values estimated in this chapter. These figures are referred to in chapter 7 when calculating hydro levelised cost values.

Technology	Climate Scenario						
	Baseline	2050 10%	2050 50%	2050 90%	2080 10%	2080 50%	2080 90%
Hydro	40.0	34.3	38.4	42.5	32.7	36.8	40.9

Table 6-16: Hydro capacity factor values

6.3 Other technologies

This study assumes that tidal stream, thermal plant and biofuels are not affected by climate due to limited resource. Refer to sections 2.3 and 9.5 for further information.

6.4 Summary of all Technology Resource Climate Variability

The analysis in Chapters 3 to 6 explored technology resource and energy output for the baseline climate and future climates for the UK. The aim of this section is to view the intra-annual changes for each of the technologies together. The following figures are all for the 2080s medium emissions. The 2050 values are not shown however, they show similar characteristics but to a lesser extent than the 2080s. Figure 6-14 shows the percentage change in energy output for each investigated technology from baseline climate to the 2080s with the medium emissions scenario. Solar clearly stands out as the only investigated technology that increases output for the 50% scenario.

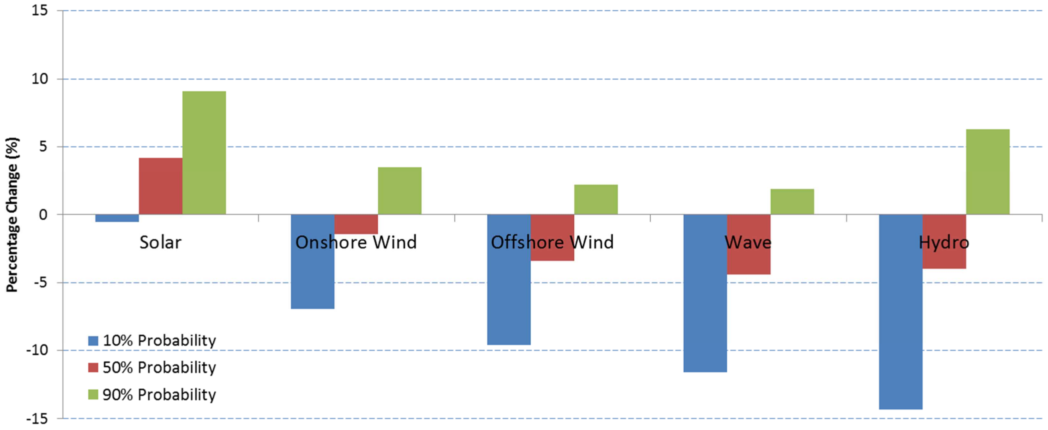


Figure 6-14: Percentage change in energy output for the 2080s

In Figure 6-15 the energy output for the baseline climate and 2080s medium emissions with 50% probability level is shown. It shows very clearly that summer months are where the largest climate energy output changes are. All investigated technologies reducing energy output except for Solar PV that increases. It also strengthens the potential importance in future solar PV energy output, not only is its availability negatively correlated with other renewables, but also that the projected changes enhance that difference.

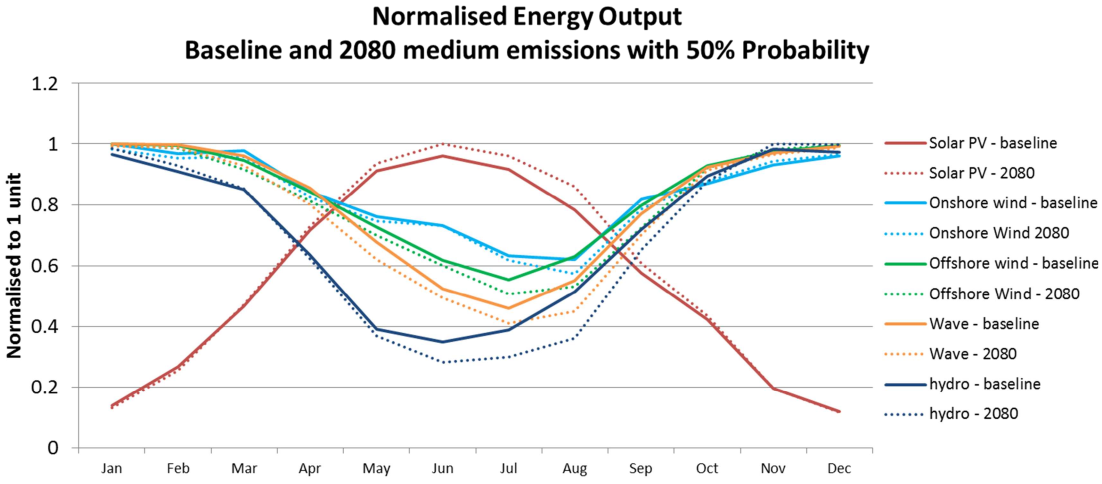


Figure 6-15: Normalised monthly energy output for baseline and 2080s (50% probability) climate

Figure 6-16 shows the energy output percentage change from the baseline to the 2080s medium emissions climate (for the 50% probability level). The lower values in winter are not necessarily due to there being less climate change in comparison to summer months. For wind and wave technologies the climate change in summer months is sensitised further by the conversion to energy process. The wind and WEC energy converters are spending more time below their rated output in summer months, where any change in climate is magnified by the cube relationship between wind speed and wind power. In summer months, Hydro is affected by reduced rainfall and increased temperatures resulting in less river flow.

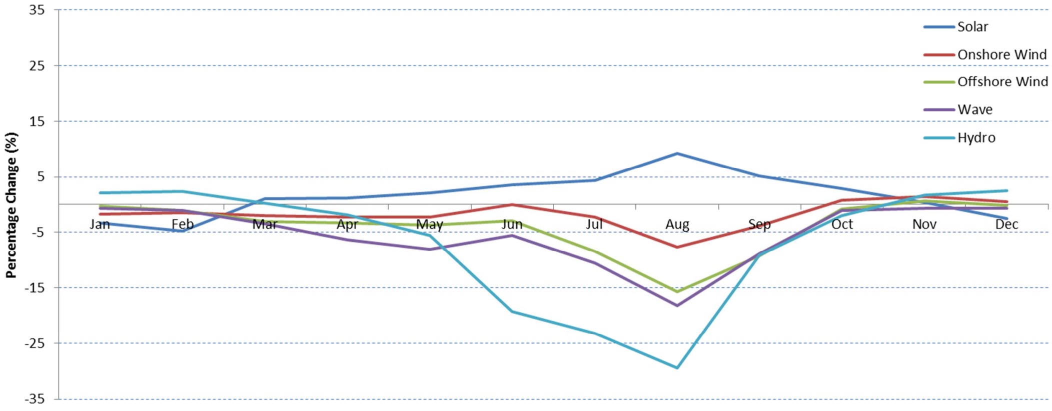


Figure 6-16: Energy output percentage change from the baseline climate to the 2080s medium emissions with 50% probability level

7 Electricity Generation Levelised Costs

7.1 Introduction

The main objective of this section is to obtain Levelised cost of electricity values (LCOE) for 2010 and 2020. The 2010 LCOE are based on a review of existing literature with some LCOE adjusted to conform to the capacity factors estimations from the previous chapters. The 2020 LCOE are based on predicted capacity factors (as 2010 in most cases) and predicted (assumed) changes (reductions) of CAPEX and OPEX. Future climate LCOE values for solar PV, wind, wave and hydro are obtained by using the future climate capacity factor estimations as stated in the summary section of each of the resource chapters. The LCOE estimations have been calculated in a way that is coherent and comparable across all of the technologies. The LCOE figures are used in the next chapter for the MVPT analysis.

The yellow blocks in the thesis flowchart (Figure 7-1) signify the areas of the thesis connected with this chapter.

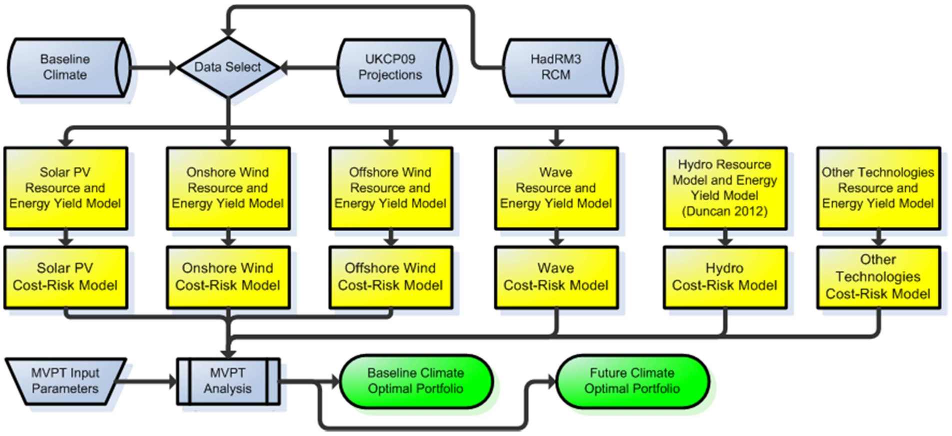


Figure 7-1: Thesis flowchart and levelised cost blocks

In section 7.3 the levelised cost values to be used in the following Mean Variance Portfolio Theory (MVPT) analysis are estimated for 2010 and 2020 technology cost projections and baseline, 2050 and 2080 climates. In essence the climate is used to alter the production levels while the technology projections alter the underlying costs.

Also included in this chapter is an investigation of the variability of the levelised cost values to the applied discount rate which is performed to highlight that the way in which levelised costs of different technologies are affected differently by the chosen discount rate.

7.2 A Review of Current and Projected Levelised Costs

The aim of this section is to explore some of the most current levelised cost estimations for different electricity generation technologies. These and their input parameters will form the basis of the levelised costs used in the portfolio analysis in the next section.

7.2.1 Main Technologies

One of the most recent levelised cost reviews for electricity generation technologies in the UK is the UK Electricity Generation Costs Update prepared for the UK Government (Mott MacDonald, 2010). The report includes comprehensive case studies for current and future levelised cost projections of all the main technologies. Input parameters are clearly documented and discussed and include future carbon emission and fuel costs based on DECC estimations. Unfortunately, wave, tidal stream and solar PV are not covered as the report concluded that those technologies were at too early a stage to have any significant deployment over the short term and was of little benefit for that particular report. Table 7-1 shows some of the levelised costs for different cases. As can be seen the report includes cases that investigate discount rate and fuel price and CO_2 cost sensitivities. The discount rate used is 10% except where 7.5% is used to show the discount rate sensitivity. Refer to Mott MacDonald (2010) for more detailed information on these levelised costs. The costs are either assumed to be a mix of ‘first of a kind’ (FOAK) and ‘nth of a kind’ (NOAK) as shown.

Projected Levelised Costs for Electricity Generation Technologies								
Technology	Total Levelised Costs (£/MWh) for Construction Date							
	2009 FOAK & NOAK	2017 FOAK & NOAK	2017 All NOAK	2023 All NOAK	2009 7.5%	2023 7.5%	2017 high fuel / CO_2	2017 low fuel / CO_2
Gas CCGT	79.7	96.5	96.5	111.9	80.4	112.9	113.2	50.5
Gas CCGT & CCS	111.4	115.8	102.6	105.5	106.5	101.1	123.8	67.7
Coal ASC	102.2	133.2	133.2	162.3	104.4	165	137.7	68.6
Coal ASC & CCS	136.2	136.8	111.9	115.5	124	104	118.2	93.3
Coal IGCC	131.2	163.6	136	164.7	124.3	163.7	140.4	72.9
Coal IGCC & CCS	143.0	142.4	107.1	110.2	128.7	100.5	113.3	90
Nuclear	97.1	93.4	67.8	67.4	76.1	53.4	68.9	66.8
Onshore Wind	87.8	86.3	86.3	85.8	77.8	71.3	86.3	86.3
Offshore Wind	148.5	145.4	112.4	111.5	136.8	93.7	112.4	112.4
Far Offshore Wind	177.4	172.9	127.9	126.9	162.3	107.6	127.9	127.9
Hydro	83.2	83.2	83.2	83.2	62.2	62.2	83.2	83.2
Large Biomass	93.2	-	-	78.4	82	70	87.9	66.4

Table 7-1: Total Levelised Cost Figures from Mott MacDonald (2010)

7.2.2 Wave and Tidal Stream Technologies

Recent work by Allan *et al.* (2010) estimates current central wave and tidal stream electricity generation levelised costs of £189.68/MWh and £81.25/MWh. The calculations are at 2006 prices, use a 10% discount rate and assume a capacity factor of 33% for both technologies. The levelised cost method has been performed in a comparable way to the method in Mott MacDonald (2010) and only needs to be converted to relate to 2010 prices. Table 7-2 are figures based on Allan *et al.* (2010) but adjusted to 2010 prices. The figures show how sensitive the technologies are to the uncertainty of construction costs. Both these technologies are in early development stages with large uncertainties in estimates of the costs of construction and deployment.

Levelised Cost of Wave and Tidal Stream Technology (£/MWh)		
Construction Cost Sensitivity	Wave	Tidal Stream
Central	208.65	89.38
Low	118.43	78.09
High	240.45	153.18

Based on Allan *et al.* (2010) adjusted to 2010 prices

Table 7-2: Wave and Tidal Stream Levelised Cost Estimates

Other recent levelised cost figures for wave and tidal stream are included in The Carbon Trust report ‘Accelerating Marine Energy’ (Carbon Trust 2011). The report sets out technology support pathways with the intention of lowering the cost of electricity generation for wave and tidal stream technologies in the UK. The report includes levelised cost projection targets which are shown in Table 7-3. The parameters used in the levelised cost calculations are not all available in the report so it is difficult to compare with other reports.

Target Levelised Costs (£/MWh)				
	Wave		Tidal Stream	
Year	Learning by Doing	Accelerated Learning	Learning by Doing	Accelerated Learning
2010	430	430	310	310
2013	300	300	250	240
2017	250	210	210	175
2020	240	180	200	150
2023	220	160	190	145
2030	195	130	175	120
2040	170	100	155	100
2050	150	80	140	80

Table 7-3: Carbon Trust (2011) levelised cost target projections.

One major difference is that the Carbon Trust assumes a higher 15% discount rate in order to take into account the added risk associated with emerging technologies. The report used 2010 prices. As can be seen the 2010 levelised cost numbers are much higher than the figures in Allan *et al.* (2010), a large proportion of this is due to the higher discount rate as renewable technologies are much more sensitive to the discount rate due to the large proportion of costs being in the construction period at the start of the project. One other cause may be the capacity factor used in the calculations. Allan *et al.* (2010) assumes 33%. It is unclear what the Carbon Trust use but it does look like it takes an average from several high and low energy locations throughout the UK and it is likely the average capacity factor used is lower than 33%.

Another source of levelised cost projections for wave and tidal stream is the ETI Roadmap (ETI 2010). The cost parameters shown below in Table 7-4 are target figures in ETI (2010) and give Cost of Energy (COE) marine energy targets of 49%, 33.1% and 24.4% relative to current COE values for the 2020s, 2030s and 2050s respectfully. The report does not distinguish between wave and tidal stream technologies and does not include all main parameters used in the levelised cost estimation. There is no indication of discount rate or operational lifetime. The CAPEX costs are in 2010 prices. As can be seen the estimated cost of electricity (COE) range is large, 2010 values range 170 to 400 £/MWh. Overall there is considerable uncertainty regarding marine energy levelised costs.

Technology and System Performance	2010	2020	2030	2050
CAPEX (£/kW)	4000-7000	2500-4000	2000-2500	1500-2000
O&M Costs (p/kWh)	1.5 – 4.0	1.0 – 2.5	0.5 – 1.5	0.3 – 1.0
Load Factor (%)	25 – 35	35 – 40	37 – 42	40 – 45
Availability (%)	75 – 85	90	90 – 95	95 – 98
Overall COE (p/kWh)	17 – 40	9 – 18	7 – 10	5 – 8
COE relative to 2010 (%)	-	49.0	33.1	24.7

Table 7-4: Marine Energy Deployment Targets (ETI 2010)

7.2.3 Solar PV Technology

Solar PV technology has been around for a while but historically is very expensive. Costs have reduced rapidly over recent years and continue to do so. Table 7-5 shows Solar PV CAPEX current cost estimations and future target estimations from IEA (2009, 2010) and Ernst and Young (2011). The IEA reports have figures for utility (>1MW), commercial (< 1 MW) and residential installations (< 20 kW). Ernst and Young have projections out to 2015 for residential systems. The CAPEX values are shown in Table 7-5 and highlights the expected reduction in cost over the next few decades. The two sets of data are broadly comparable.

CAPEX Projected Costs of Solar PV systems (p/kW)				
	IEA (2010a, 2010b)			Ernst & Young (2011)
Year	Utility (starting at 1MW)	Commercial (up to 1MW)	Residential (up to 20kW)	Residential (up to 20kW)
2008	21.59	26.99	32.39	
2011	-	-	-	27.00
2015	-	-	-	15.50
2020	9.72	12.15	14.57	-
2030	6.48	8.10	9.72	-
2050	4.32	5.40	6.48	-

Table 7-5: CAPEX costs for Solar PV from IEA (2010a, 2010b) and Ernst & Young (2011)

Solar PV levelised cost estimates have been calculated using the CAPEX costs from Table 7-5 and the main cost assumptions from Table 7-6. The O&M costs have been assumed to be 1% of capital cost per annum as in both reports.

Solar PV cost assumptions for levelised cost estimations	
Discount Rate	10%, (5%, 15%)
Capacity (MW)	1 MW
O&M (£/MWh)	1% of CAPEX per annum
Load factor (%)	14.1 %
Lead time (years)	1 year
Expected lifetime (years)	25yrs (2010); 30yrs (2020); 35yrs(2030) 40yrs(2050)

Table 7-6: Primary cost assumptions for estimation of Solar PV levelised cost for the UK

The solar PV levelised cost calculations are shown in Table 7-7 and have been calculated using CAPEX projected costs from Table 7-5 and inputs that allow the costs to be comparable to the levelised costs in Table 7-1 and Table 7-2. The load factor has been based on data from the UK solar model in chapter 3. The operational lifetime increases over each time period from a current 25 years to 40 years by 2050. The discount rate used is 10%, also shown in brackets are values for 5% and 15% discount rates to bring attention to how sensitive solar PV levelised costs are to the discount rate.

Levelised Costs (£/MWh at 10% (5%, 15%) Discount Rate				
	IEA (2010)			Ernst & Young (2011)
Year	Utility (starting at 1MW)	Commercial (up to 1MW)	Residential (up to 20kW)	Residential (up to 20kW)
2008	219.4 (147.8, 300.7)	274.3 (184.7, 375.9)	329.1 (221.7, 451.1)	
2011	-	-	-	274.4 (184.8, 376.0)
2015	-	-	-	157.5 (106.1, 215.9)
2020	95.4 (61.7, 133.4)	123.4 (83.2, 169.2)	148.1 (99.7, 203.0)	-
2030	65.8 (44.3, 90.2)	82.2 (55.4, 112.7)	98.7 (66.5, 135.3)	-
2050	43.9 (29.6, 60.1)	54.9 (37.0, 75.2)	65.8 (44.4, 90.2)	-

Table 7-7: Projected Levelised Costs Estimations for Solar PV

The O&M proportion of the total levelised cost is shown in Table 7-8 and will be used in the portfolio theory calculations.

O&M Percentage of Total Levelised Cost (%)		
Operating Life	Discount Rate	Percentage of Total Levelised Cost
25	10 (5, 15)	8.3 (12.4, 6.1)
30	10 (5, 15)	8.6 (13.3, 6.2)
35	10 (5, 15)	8.8 (14.1, 6.2)
40	10 (5, 15)	8.9 (14.6, 6.2)

Table 7-8: O&M percentage of total levelised costs for different variables

7.2.4 Levelised Cost Comparison and Sensitivity to Discount Rate

In this section levelised costs are generated for each technology using common input parameters as used in Mott MacDonald (2020), Allan *et al.* (2010), IEA (2010), Ernst and Young (2011). Gas, coal, nuclear, hydro and biomass input data are based on data from Mott MacDonald (2010). Wave and tidal stream values are based on values from Allan *et al.* (2010). Solar PV values are based on CAPEX and O&M values from IEA (2010) and capacity factor values from Chapter 3. The levelised cost values are shown in Figure 7-2. The overall values have been broken into different cost components. The levelised cost estimates are based on input parameters from three different sources but have been calculated using an identical process so they are comparable.

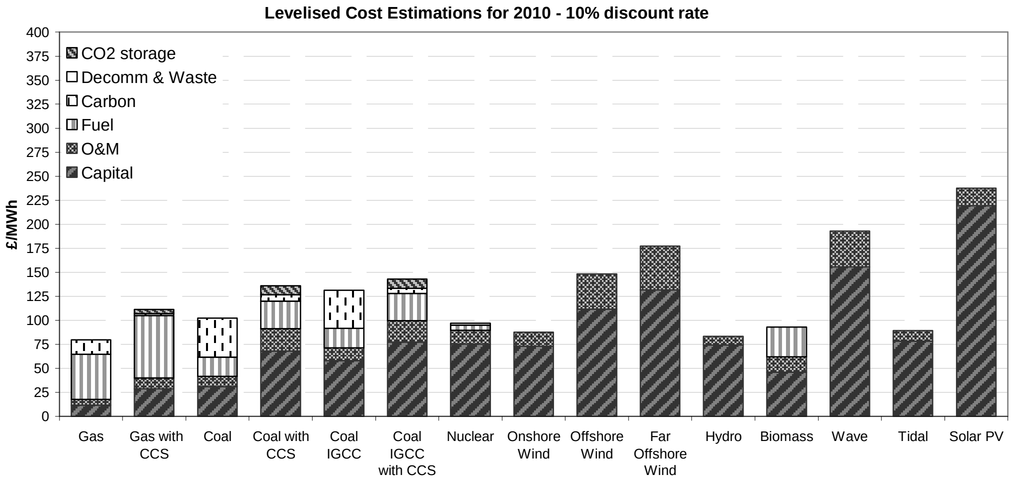


Figure 7-2: Levelised costs for different technologies for 2010 with 10% discount rate

5.1.1.1 Discount Rate Sensitivity

As previously mentioned, the discount rate can significantly affect the levelised cost. The MVPT analysis in Chapter 8 is performed using a discount rate of 10%. However, this section is intended to demonstrate the sensitivity of different technology levelised costs to the discount rate used. Figure 7-3 and Figure 7-4 use the same input parameters as Figure 7-2 but are calculated using 5% and 15% discount rate values instead of 10%.

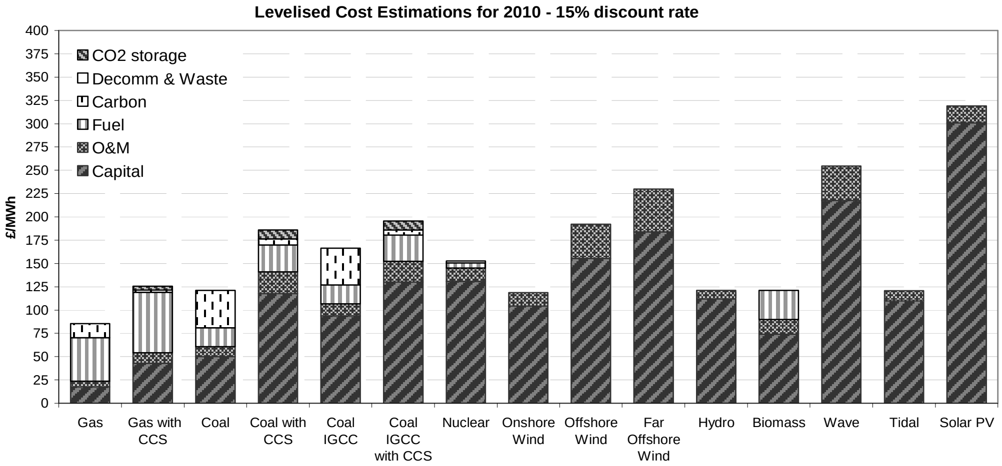


Figure 7-3: Levelised costs for different technologies for 2010 with 15% discount rate

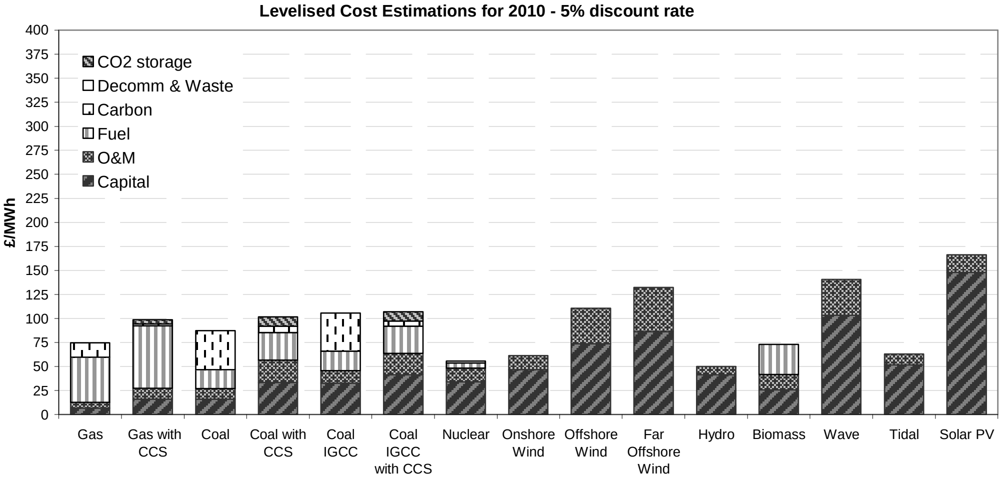


Figure 7-4: Levelised costs for different technologies for 2010 with 5% discount rate

When looking at the change in the different cost components it is very clear that the fraction of LCOE due to initial costs is most sensitive to discount rate; whereas, costs that are spread relatively evenly over the plant operating life are not affected. It is worth noting that the output is discounted as well as the input costs and so a constant ratio value will be returned when an even distribution of operating costs and output are assumed.

The technologies that have a high ratio of CAPEX against their overall costs are most sensitive to discount rates; for example, Solar PV with a discount rate of 5% has a cost of £148/MWh and doubles to £301/MWh when a 15% discount rate is assumed. In comparison, Gas - which has comparatively low initial costs and higher operating costs - jumps a mere 14% from £75/MWh to £85.5/MWh.

Fuel is the largest proportion of costs for fossil fuel technologies but unlike construction costs, all future fuel costs are discounted to their present value and this can arguably give fossil fuel technologies an advantage over more capital intensive renewables when comparing using levelised costs, especially when a high discount rate is utilised in the levelised cost projections. One of the key arguments by Awerbuch is that the discount rate applied to fuel costs is inadequate to compensate for fuel price variability. Renewables are much more competitive when a lower discount rate is assumed.

7.3 Levelised Cost Values for Portfolio Analysis

The levelised costs to be used in the portfolio analysis will be discussed and stated in this section. In the previous section all levelised costs, except solar PV, were calculated using assumed load factors (or capacity factors) from Mott MacDonald (2010) and Allan *et al.* (2010). The levelised costs for solar PV, onshore and offshore wind will be based on analyses output from chapters 3, 4 and 5 respectively. The levelised costs for hydro will be generated using the Mott MacDonald (2010) assumed load factors; the future climate sensitivity is based on the relative climate sensitivities from chapter 6. There are several sets of levelised costs generated for different time periods, these capture projected cost parameters as well as projected climate changes that affect the resource and subsequently the levelised cost. To simplify matters this study will assume that only solar PV wind, wave and hydro resource is affected by climate variability as discussed in Chapter 6. The work aims to be as ‘internally consistent’ as possible in attempting to ensure technology and climate scenarios are aligned. One reason for sensitivity to changes is high costs, particularly CAPEX. It is an assumption that changing cost profiles for renewables will alter their vulnerability / sensitivity to climate change.

To capture the range of outcomes, levelised costs are calculated not only for 2010 but also for 2020 and 2050 based on projected changes in underlying costs. In addition each set of costs are subject to a range of climates covering ‘current’, 2050s and 2080s.. The future climate sets of levelised costs have 3 probability level values (10%, 50%, 90%). All sets of levelised cost values are based on the capacity factor figures shown in Table 7-9.

Technology	Climate Scenario						
	Baseline	2050 10%	2050 50%	2050 90%	2080 10%	2080 50%	2080 90%
Solar PV	13.5	13.4	13.9	14.5	13.4	14.2	15.0
Onshore Wind	35.1	33.2	35.0	36.6	32.8	34.6	36.4
Offshore Wind	39.2	36.2	38.4	40.3	35.4	37.9	40.1
Wave	33.0	30.1	32.1	33.9	29.1	31.6	33.7
Hydro	40.0	34.3	38.4	42.5	32.7	36.8	40.9

Table 7-9: Capacity factors used in levelised cost calculations

7.3.1 Levelised Costs based on 2010 Input Cost Parameters

This section discusses the sets of levelised cost values based on technology cost projections for 2010. There are three sets of levelised cost values.

7.3.1.1 Output with Baseline Climate

Only onshore and offshore wind values change from the levelised cost values shown in Figure 7-2. Wave energy levelised costs have been calculated using a capacity factor estimation from Allan *et al.* (2010) rather than the resource estimations from Chapter 6.1, which have been based on a power conversion profile of an early Pelamis prototype and considered to be a low estimation of capacity factor.

The wind energy values have been recalculated using baseline capacity factor values from chapters 4 and 5, as shown in Table 7-10.

Comparison of Capacity Factor Values	
Onshore Wind	
Mott MacDonald (2010)	28.0%
'This Study' Burnett (2012) – baseline	35.1%
Offshore Wind	
Mott MacDonald (2010)	39.0%
'This Study' Burnett (2012) – baseline	39.2%

Table 7-10: Average UK wind load factor values

Table 7-11 and Figure 7-5 show the revised levelised costs based on a discount rate of 10% with the inclusion of the revised wind energy values.

Projected 2010 levelised costs with 10% Discount Rate (£/MWh)							
	Capital	O&M	Fuel	Carbon	Decomm & Waste	CO_2 Storage	TOTAL
Gas	11.8	6.0	15.1	46.9	-	-	79.7
Gas & CCS	28.7	11.3	2.1	65	-	4.3	111.4
Coal	31.2	10.8	40.4	19.9	-	-	102.2
Coal & CCS	68.1	23.3	6.5	28.7	-	9.6	136.2
Coal IGCC	58.3	13.1	39.6	20.3	-	-	131.2
Coal IGCC & CCS	77.4	22.3	5.5	28.3	-	9.5	143.0
Nuclear	75.5	14.3	-	5.25	2.05	-	97.1
Onshore Wind	73.2	14.6	-	-	-	-	87.8
Offshore Wind	111.7	36.7	-	-	-	-	148.4
Far Offshore Wind	131.6	45.8	-	-	-	-	177.4
Hydro	74.2	9.0	-	-	-	-	83.2
Biomass	46.1	15.9	-	31.2	-	-	93.2
Wave	155.6	37.4	-	-	-	-	193.0
Tidal Stream	78.2	11.2	0	0	0	0	89.4
Solar PV	219.4	18.3	0	0	0	0	237.7

Table 7-11: Revised 2010 levelised costs at 10% discount rate (£/MWh)

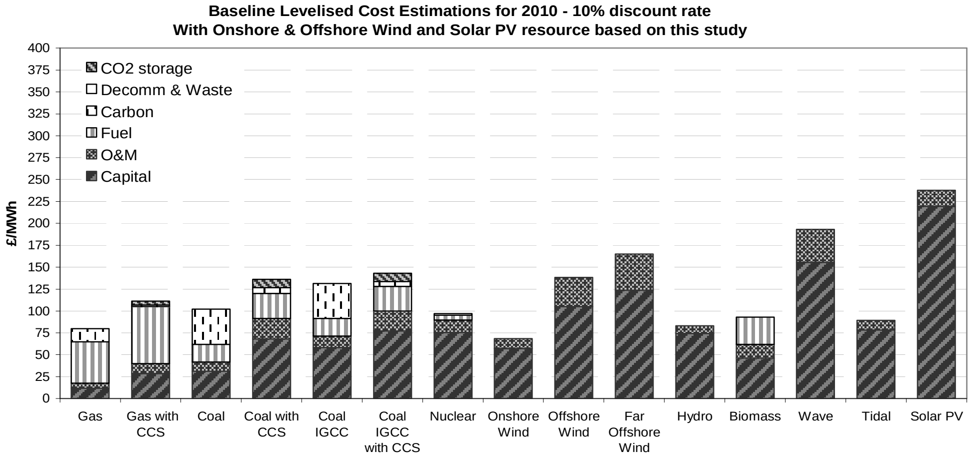


Figure 7-5: Revised projected 2010 Baseline levelised costs at 10% discount rate

5.1.1.2 Energy output based on the 2050s and 2080s climate

This section re-calculates levelised costs for 2010 technology costs based on the 2050s and 2080s capacity factor values shown in Table 7-9. The levelised cost change (from baseline values) for the 2050s and 2080s climate are shown in Table 7-12. All, except solar PV, increase in cost for the 2050s and 2080s for the 50% probability level. Hydro has the largest cost change of 11% for the 2080s climate, wave increases by 4.6%, offshore wind by 3.4%, onshore wind by 1.4% and finally solar PV reduces in cost by 3.7%.

Projected 2010 Levelised Costs Probability Level (%) = 50 (10, 90)			
	Capital (£/MWh)	O&M (£/MWh)	TOTAL (£/MWh)
Solar PV			
Baseline Climate	219.4	18.3	237.7
2050s Climate	213.1 (220.8, 205.4)	17.7 (18.4, 17.0	230.8 (239.2, 222.4)
2080s Climate	211.3 (220.3, 202.6)	17.6 (18.4, 16.8)	228.8 (238.7, 219.4)
Onshore Wind			
Baseline Climate	73.2	14.6	87.8
2050s Climate	73.4 (76.5, 70.8)	14.6 (14.1, 15.2)	88.0 (91.7, 85.0)
2080s Climate	77.2 (76.5, 70.9)	14.8 (14.2, 15.4)	88.8 (92.6, 85.4)
Offshore Wind			
Baseline Climate	111.7	36.7	148.4
2050s Climate	113.9 (120.4, 108.8)	37.4 (39.5, 35.8)	151.3 (159.9, 144.6)
2080s Climate	115.3 (123.0, 109.3)	37.8 (40.3, 36.0)	153.2 (163.2, 145.3)
Far Offshore Wind			
Baseline Climate	131.6	45.8	177.4
2050s Climate	134.2 (141.9, 128.2)	46.7 (49.2, 44.7)	180.8 (191.1, 172.9)
2080s Climate	135.9 (144.9, 128.8)	47.2 (50.2, 44.9)	183.1 (195.1, 173.7)
Wave			
Baseline Climate	155.6	37.4	193.0
2050s Climate	160.0 (170.5, 151.4)	38.5 (41.0, 36.4)	198.4 (211.5, 187.8)
2080s Climate	162.8 (176.2, 152.5)	39.1 (42.4, 36.7)	201.9 (218.6, 189.4)
Hydro			
Baseline Climate	74.2	9.0	83.2
2050s Climate	78.1 (87.3, 69.0)	9.5 (10.6, 8.4)	87.6 (97.9, 77.4)
2080s Climate	82.4 (92.7, 70.6)	10.0 (11.3, 8.6)	92.4 (104.0, 79.2)

Table 7-12: 2010 technology levelised costs change from baseline for 2050s and 2080s medium emissions climates (£/MWh)

7.3.2 Levelised Costs based on 2020s Projected Input Cost Parameters

This section discusses the sets of levelised cost values based on technology cost projections for 2020. The 2020 projected levelised costs of technologies assumed not to be affected by climate change are shown in Table 7-13 and are based on figures from Mott MacDonald (2010).

Projected 2020 levelised costs with 10% Discount Rate (£/MWh) Baseline Climate							
	Capital	O&M	Fuel	Carbon	Decomm & Waste	CO2 Storage	TOTAL
Gas	11.1	6.0	50.9	44.0	-	-	112.0
Gas & CCS	20.5	9.6	65.9	6.0	-	3.5	105.5
Coal	28.4	10.8	19.9	103.2	-	-	162.3
Coal & CCS	47.4	17.5	27.6	15.6	-	7.4	115.5
Coal IGCC	33.0	10.7	19.6	101.4	-	-	164.7
Coal IGCC & CCS	45.5	15.9	27.2	14.1	-	7.5	110.2
Nuclear	49.2	10.9	5.2	-	2.1	-	67.4

Table 7-13: Revised projected 2020 levelised costs at 10% discount rate with baseline climate

7.3.2.1 Tidal Stream Energy

Tidal stream resource is also assumed to be unaffected by climate change. It was not included in the Mott MacDonald (2010) report. Instead, future 2020 projected costs are estimated based on figures in Allan *et al.* (2010) as shown in Table 7-2, Carbon Trust (2011) future levelised cost targets as shown in Table 7-3; and target projections from the ETI Roadmap (ETI 2010) as shown in Table 7-4. The Carbon Trust (2010) estimate LCOE reductions in the range of 39% and 54% for ‘Learning by Doing’ and ‘Accelerated Learning’ by the 2020s. ETI (2010) estimate 2020 cost of electricity figures to be in the range of 49% of 2010 values. All above figures are applicable to wave energy as well as tidal stream energy. This study assumes reductions in the region of 40% in capital and O&M costs of tidal stream by 2020. The resulting estimated 2020 levelised costs based on future climate capacity factors (Table 7-9) are shown in Table 7-14.

7.3.2.2 Wave Energy

Wave Energy resource and its levelised cost sensitivity to climate change have been discussed in section 7.2.2. Projected 2020 levelised costs for a baseline climate and 2050s and 2080s medium emissions with 50% probability climate have been estimated using the same cost reductions assumed for tidal stream and capacity factors from Table 7-9. The values are shown in Table 7-14. The future costs increase due to the reduction of future capacity factor from a baseline value of 33.0% to 32.1% and 31.6% for the 2050s and 2080s with 50% probability level respectively

7.3.2.3 Onshore and Offshore Wind Energy

Both Onshore and Offshore Wind Energy projected 2020 costs use input parameters from the Mott MacDonald (2010) and capacity factor estimations from this study. The Mott MacDonald report estimates central construction costs in 2020 to be in the region of 96%, 80% and 75% of 2010 costs respectively for onshore, offshore, and far offshore wind energy. Levelised costs for onshore, offshore and far offshore wind using the above construction costs and capacity factors from Table 7-9 are shown in Table 7-14. The future costs increase due to a reduction of capacity factor for both on and offshore wind.

7.3.2.4 Solar PV

Projected utility CAPEX costs for 2020 published in IEA (2010, 2011) and previously shown in Table 7-5 have been used for estimating projected levelised costs for solar PV (Table 7-14) based on the capacity factors from Table 7-9. The future costs for solar PV reduce due to the increase in capacity factor.

7.3.2.5 Hydro

The projected hydro 2020 costs for the baseline climate assumed unchanged from the 2009 costs as in (Mott MacDonald 2010). As mentioned previously, the hydro levelised cost estimates performed in this thesis uses the assumed Mott MacDonald capacity factor for the baseline and adjusts the value for the future climate using the relative capacity factor changes from section 6.2. The 2020 levelised costs for the baseline, 2050s and 2080s climate capacity factors (Table 7-9) are shown in Table 7-14. The future climate hydro costs increase due to a reduction of capacity factor.

Projected 2020 Levelised Costs Probability Level (%) = 50 (10, 90)			
	Capital (£/MWh)	O&M (£/MWh)	TOTAL (£/MWh)
Solar PV			
Baseline Climate	87.2	8.2	95.4
2050s Climate	80.8 (73.2, 88.6)	7.6 (6.9, 8.3)	88.4 (80.1, 96.9)
2080s Climate	79.0 (70.1, 88.1)	7.5 (6.7, 8.3)	86.5 (76.8, 96.4)
Onshore Wind			
Baseline Climate	54.7	10.9	65.6
2050s Climate	54.9 (52.3, 58.0)	11.0 (10.4, 11.5)	65.9 (62.7, 69.5)
2080s Climate	55.5 (52.7, 58.7)	11.1 (10.5, 11.7)	66.6 (63.2, 70.4)
Offshore Wind			
Baseline Climate	84.2	32.8	117.0
2050s Climate	86.4 (81.3, 92.9)	33.5 (31.9, 35.6)	119.9 (113.2, 128.5)
2080s Climate	87.8 (81.8, 95.5)	34.0 (32.0, 36.4)	121.8 (113.8, 131.9)
Far Offshore Wind			
Baseline Climate	93.4	34.3	127.7
2050s Climate	96.0 (90.0, 103.7)	35.2 (33.2, 37.7)	130.3 (123.2, 141,4)
2080s Climate	97.6 (90.6, 106.7)	35.7 (33.4, 38.7)	133.3 (124.0, 145.4)
Wave			
Baseline Climate	93.4	24.3	117.7
2050s Climate	97.7 (89.2, 108.3)	25.3 (23.3, 27.9)	123.0 (112.5, 136.2)
2080s Climate	100.6 (90.3, 114.0)	26.0 (23.6, 29.3)	126.6 (113.6, 143.3)
Hydro			
Baseline Climate	74.2	9.0	83.2
2050s Climate	77.3 (69.9, 86.6)	9.3 (8.4, 10.5)	86.6 (78.3, 97.7)
2080s Climate	80.7 (72.6 , 90.8)	9.7 (8.8 , 11.0)	90.4 (81.3 , 101.7)

Table 7-14: Revised projected 2020 levelised costs for different climate scenarios (£/MWh)

Figure 7-6 shows all the 2020 levelised cost estimations for the baseline climate.

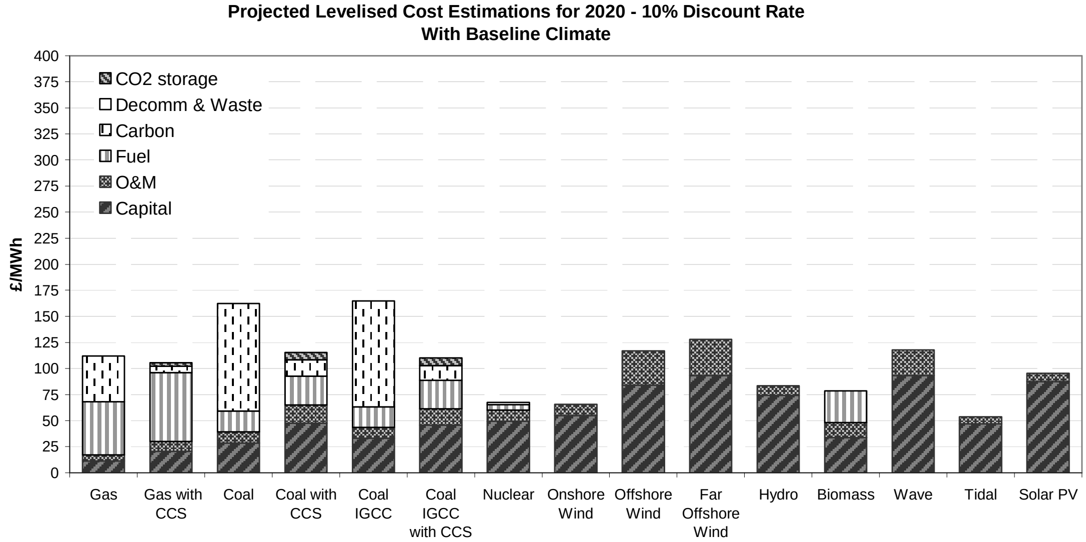


Figure 7-6: Revised projected 2020 levelised costs at 10% discount rate

7.3.3 Levelised Costs for 2050s Projected Input Cost Parameters

For the purpose of this study the levelised costs in the 2050s are assumed to be identical to the 2020 costs. It is was considered that there is too much uncertainty in attempting to estimate technology costs so far into the future and there is little literature on 2050 technology costs, especially literature that is comparable across the different technologies. If it had been decided to generate comparable levelised costs for the 2050s the following studies would be likely to provide much of the background information to generate them: ETI (2010), IEA (2010, 2011), Carbon Trust (2010) and UKERC 2050 (UKERC 2009), they all contain studies of cost targets, roadmaps, or accelerated learning targets for 2050.

There are limitations in doing this, such as having to assume that fuel and CO_2 costs are stationary, all technologies have reached maturity by 2020, and all further cost savings (between 2020 and 2050) are uniform across all technologies. However, there are also benefits, such as avoiding further cost uncertainty connected with 2050 costs calculations for each technology and the added detail attained in this study by including cost projections and optimal mixes for the 2050s that can be investigated for their sensitivity to climate change. It is evident that this is an area for further study.

7.4 Levelised Costs Summary

An extensive literature review of levelised costs of electricity generation has been undertaken. Levelised cost values and their input parameters from several different reports have been studied.

2010 LCOE Process: The 2010 LCOE figures were based on a review of existing literature with some of the LCOE adjusted to conform to the capacity factors estimated in the previous resource chapters. LCOE values for solar PV wind, wave and hydro were also estimated for the 2050s and 2080s medium emissions scenarios using capacity factors estimated on the future climate resource.

2020 LCOE Process: The 2020 LCOE are based on predicted capacity factors (as 2010 in most cases) and predicted (assumed) changes (reductions) of CAPEX and OPEX. LCOE values for solar PV wind, wave and hydro were also estimated for the 2050s and 2080s medium emissions scenarios using capacity factors estimated on the future climate resource.

2050 LCOE Process: The 2050 LCOE process used the same process as the 2020s and assumes the 2050 costs to be comparable across the technologies to the 2020 values (see section 7.3.3).

Several sets of levelised cost values specifically for this study and for use in the MVPT chapter, have been calculated from a common set of input parameters that allow all technologies to be comparable with one another.

Levelised costs for onshore wind, offshore wind and solar PV are calculated using baseline and future climate resource estimations performed in this study. Hydro and wave levelised cost values have been estimated using baseline resource values from Mott MacDonald (2010) and Allan *et al.* (2010) respectively and climate variability values from (Duncan 2012) and calculations in this study, respectively.

The levelised cost of solar PV reduces significantly by 2020. This is largely due to manufacturing cost reductions and efficiency improvements (IEA 2010a, 2010b). In 2010 it's levelised cost is significantly higher than others, almost twice the cost of offshore wind in 2010. By 2020 solar PV has a lower cost than offshore wind and is favourably comparable to some other technologies. Coal and gas both increase by roughly 50% as a result of increased fuel and CO_2 prices that are incorporated in the Mott MacDonald (2010) projected costs.

8 Application of Mean Variance Portfolio Theory

8.1 Introduction

The main objective of this chapter is to assess the sensitivity of optimal portfolios of electricity generation technologies to the effects of climate change. The information and data developed and explored in previous chapters is drawn together as input to the Mean Variance Portfolio Theory analysis.

The yellow and green blocks in the thesis flowchart (Figure 8-1) signify the areas of the thesis connected with this chapter.

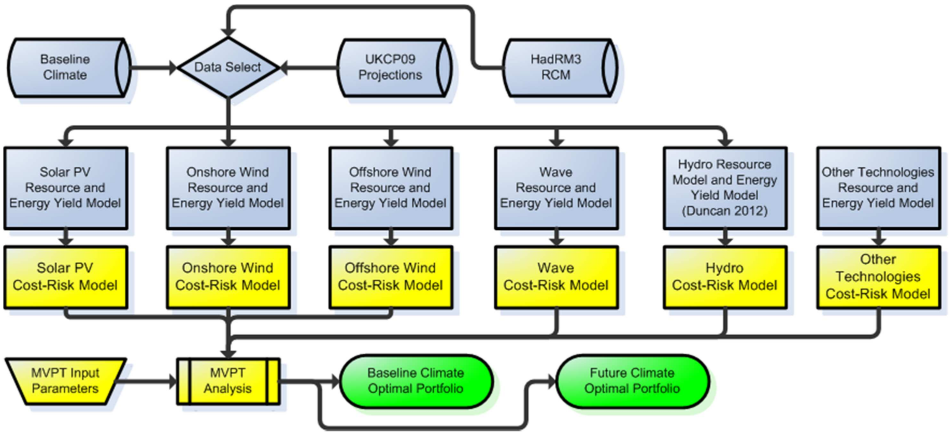


Figure 8-1: Thesis flowchart and levelised cost blocks

The MVPT analysis includes 2010 and 2020 technology cost projections with baseline and future probabilistic climate projections. In this way it follows the levelised cost analysis in Chapter 7. The analysis also explores the influence of technical and other physical constraints on the upper limits of energy share for each technology.

The first part of the chapter investigates the additional data required to compute optimal electricity generation portfolios using MVPT. Technology risk estimates, correlation coefficients and physical constraints on individual technologies are discussed and assigned values. After the input parameters have been set, the individual technology cost-risk characteristics for the baseline climate are projected on a cost-risk graph. This is done for both 2010 and 2020 projected levelised cost estimations (section 7.3). The climate variability impact on the levelised costs for the 2050s and 2080s are shown on further cost-risk graphs for the 2010 and 2020 projected levelised costs.

MVPT is used to generate efficient frontiers for the baseline climate and 2010 and 2020 cost projections respectively. The efficient frontier lines are generated using different sets of physical constraints on the share of each technology in the energy mix (2010, 2020, 2050 and no constraints). Each of the efficient frontiers are explored with emphasis on the optimal mixes at various points on the curve.

The collective technology impact of climate change on the efficient frontier using 2020 costs and 2020 constraints are investigated by generating additional curves for the 2050s and 2080s climate with probability levels of 10%, 50% and 90%, using the 2020 levelised costs of all technologies that are affected by climate change.

Finally, the sensitivity of each technology on the MVPT optimal mixes are investigated by varying the levelised cost of each technology in turn from its baseline value to future climate values and investigating the changes to the efficient frontier and optimal mixes.

8.2 MVPT Input Parameters

As discussed in chapter 2, there are input parameters that need to be ascertained before MVPT analysis can be performed. This section discusses and identifies the input parameters used in the MVPT analysis.

8.2.1 Technology Risk and Cost Correlation

Technology risk, fuel cost correlation, and O&M cost correlation values are taken directly from two sources of recent portfolio theory literature: Awerbuch and Yang (2007), and Allan *et al.* (2011). Allan largely follows the Awerbuch assumptions and adds values for wave and tidal stream technologies.

Table 7-1 shows the technology risk estimates, they are a measure of the fluctuation of the cost streams and expressed as “the standard deviations of the holding-period returns based on historical data for each cost component” (Awerbuch and Yang 2007).

Capital Cost Risk (construction): This depends on the complexity and construction time period of the technology. Much of these numbers are from a World Bank analysis. The numbers for emerging renewable technologies come from developer interviews (Awerbuch and Yang 2007).

Fuel Cost Risk: These figures are based on historical European fossil fuel import prices from 1980 to 2005.

Operation and maintenance risk: These figures are difficult to estimate. These are typically available from corporate records but not publicly available. (Awerbuch and Yang 2007) uses The US Energy Information Agency and the Federal Regulatory Commission databases which include records for all generators operated by a regulated utility.

Technology	Construction	Fuel	O&M	Pre-Development	Fuel Delivery	Waste Fund	Storage
Wave	10	-	8	10	-	-	-
Tidal Stream	10	-	8	10	-	-	-
Onshore Wind	5	-	8	5	-	-	-
Offshore Wind	10	-	8	10	-	-	-
Nuclear	23	24	5.5	23	-	10	-
Gas	15	19	10.5	-	19	-	-
Coal	23	14	5.4	-	14	-	-
Hydro	38	-	15.3	-	-	-	-
Biomass	20	18	10.8	-	-	-	-
Coal with CCS	23	14	5.4	-	14	-	40
Gas with CCS	15	19	10.5	-	19	-	40
Solar PV	5	-	3.4	-	-	-	-

Table 8-1: Technology Cost Component standard deviation. Source Awerbuch & Yang (2007); Allan *et al.* (2011)

Correlation Coefficients: As previously mentioned, the correlations between fuel and O&M cost components of each technology have also been taken directly from Awerbuch and Yang (2007) and Allan *et al.* (2011). Table 8-2 shows the historic fuel price correlation coefficients. These are based on a historical fuel price series for the UK (Allan *et al.* 2011, Awerbuch and Yang 2007)

Fuel Price Correlation	Gas	Gas & CCS	Coal	Coal with CCS	Nuclear	Biomass
Gas	1	1	0.757[a]	0.757[a]	0.649[a]	-0.44[b]
Gas & CCS	-	1	0.757[a]	0.757[a]	0.649[a]	-0.44[b]
Coal	-	-	1	1	0.591[a]	-0.38[b]
Coal & CCS	-	-	-	1	0.591[a]	-0.38[b]
Nuclear	-	-	-	-	1	-0.22[b]
Biomass	-	-	-	-	-	1

[a] indicates that these estimates are taken from Allan *et al.* (2010)
[b] indicates that these estimates were taken from Awerbuch and Yang (2007)

Table 8-2: Fuel price correlation coefficients.

Table 8-3 shows the O&M correlations. These figures have been taken from Awerbuch and Yang (2007) and calculated from holding-period returns (HPR).

O&M Correlation	Gas	Gas CCS	Coal	Coal CCS	Nuclear	Wind	Hydro	Biomass	Wave	Tidal Stream	Solar PV
Gas	1	1	0.25	0.25	0.24	0	-0.04	0.32	0	0	0.05
Gas CCS		1	0.25	0.25	0.24	0	-0.04	0.32	0	0	0.05
Coal			1	1	0	-0.22	0.30	0.18	-0.22	-0.22	-0.39
Coal CCS				1	0	-0.22	0.30	0.18	-0.22	-0.22	-0.39
Nuclear					1	-0.07	-0.41	0.65	-0.07	-0.07	0.35
Wind						1	0.29	-0.18	0	0	0.05
Hydro							1	-0.18	0	0	0.30
Biomass								1	0	0	0.25
Wave									1	1	0.05
Tidal Stream										1	0.05
Solar PV											0.05

Source: Awerbuch and Yang (2007)

Table 8-3: Operation and maintenance cost correlation coefficients

The figures on costs are ultimately uncertain. As such, they will add error to the portfolio analysis, but it is not possible to clarify their extent. While this is an input consideration, the main effort is in identifying and isolating the impact of climate change. Estimating the spread in cost and risk and the impact on optimal portfolios is evidently an area for future work.

8.2.2 Technology Mix Constraints

When portfolio theory is applied to electricity generation the use of constraints are typically needed to control the physical upper limits of each technology, which is a product of the maximum deployment level of that technology, its resource or its ability to match demand. MVPT literature generally used only one set of constraints. This study encompasses these and uses five sets of constraint scenarios to represent different time periods and to explore the sensitivity of optimal MVPT mixes to the chosen technology constraints. The 5 chosen constraint scenarios are shown in Table 8-4 and explained as follows:

The 2010 ‘tight’ upper constraints are intended to represent roughly what is practically possible at this time and have been deliberately bound very close to the 2009 electricity generation mix. The 2010 ‘looser’ constraints are intended to increase renewables share slightly beyond their current physical limitations.

The 2020s and 2050s constraints are subjective and for some of the emerging technologies are very ambitious; however, it is thought, for the benefits of this study, that they have been set appropriately. The 2020 upper constraints are based largely on information in Awerbuch and Yang (2007), the UK Renewable Energy Roadmap (DECC 2011) and DUKES (2010). There is more uncertainty with setting upper constraints for the 2050s and so two sets of 2050 constraints have been generated as different potential scenarios. The first set (2050) is based loosely on reports investigating energy systems pathways towards 2050 (Anandarajag *et al.* 2009, DECC 2010, Winskel *et al.* 2009). The second set (2050 20%) has all technologies at a maximum 20% of total energy supply, except for coal and gas without CCS which is set to 5% so as to meet 2050 CO_2 reduction targets. The 2050s constraints loosely correspond to a large percentage of nuclear and a diversified future. In all cases, the lower limits have all been set to 0%.

Technology	2009 UK mix (%) approximately	Upper Constraint 2010 Tight (%)	Upper Constraint 2010 Loose (%)	Upper Constraint 2020 (%)	Upper Constraint 2050 (%)	Upper Constraint 2050 20% (%)
Gas	44.5	50	50	39	5	5
Gas & CCS	0	0	0	1	30	20
Coal	28.1	35	35	34	5	5
Coal & CCS	0	0	0	1	30	20
Nuclear	18.6	25	25	20	50	20
Onshore Wind	2.03	2.5	12.0	12.0	15	20
Offshore Wind	1.47	2.0	10.0	10	15	20
Far Offshore Wind	0	0	5.0	10	15	20
Hydro	1.41	2.0	5.0	5.0	5.0	20
Biomass	2.86	4.0	10.0	10	10	20
Wave	0	0	2.5	2.5	10	20
Tidal Stream	0	0	2.5	2.5	5	20
Solar PV	0.005	0.01	2.5	2.5	10	20

Table 8-4: Applicable technologies in the 2010 mix and their constraints (proportion of total generated energy)

The assumed 2020s electricity demand is set at 400 TWh based on forecasts in DECC (2010) for future pathways α, β and γ. In 2009 there was 372 TWh of electricity generated (DUKES 2011). There are many studies investigating possible future electricity generation scenarios towards 2050 (AEA Technology 2011, DECC 2010, Winskel et al. 2009). The 2050 demand estimations vary quite considerably (in the region of 275-600 TWh) depending on the future outcome scenario. This thesis has assumed a central estimate of 500 TWh, an increase from 2020 due to a larger population and transport electrification associated with substantial energy efficiency efforts.

8.2.3 Technology Cost and Risk Variability

The levelised costs and risks of each technology for 2010 cost and baseline climate projections are shown in Figure 8-2. Although hydro is the cheapest of the renewables, it is also the riskiest of all technologies due to the financial risk in its construction period. Solar PV is by the most expensive but also the least risky. The fossil fuel technologies are all in the mid-range of cost and risk. Coal and gas CCS are significantly more expensive than their non-CCS counterparts. Solar PV clearly stands out as being different from the trend of the others in shifting towards a lower cost with future annual average climate variability; whereas the others are weighted towards an increase in cost. The variability shown in red is the 2050s annual average climate variability for the 10% and 90% climate probability levels and the 50% is shown as a horizontal red mark.

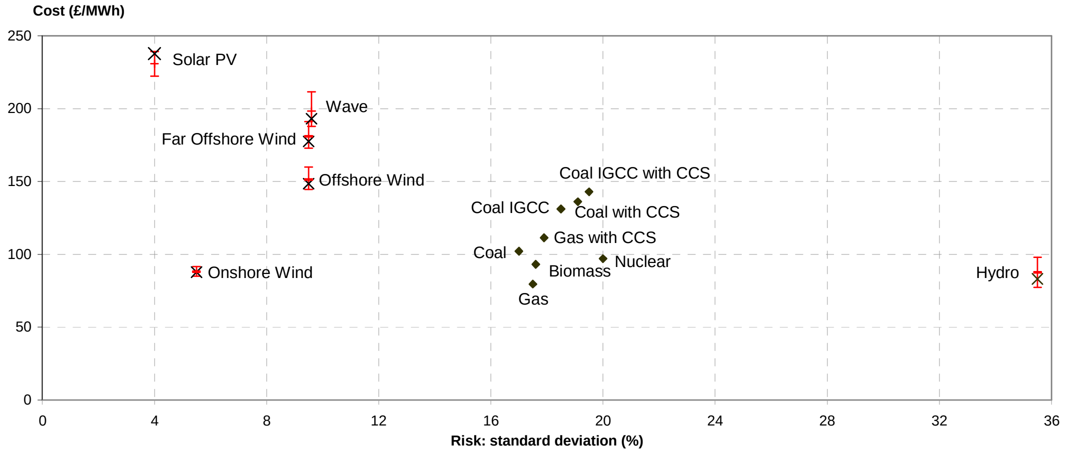


Figure 8-2: Cost Risk Graph for 2010 Cost Projections with baseline (black) and 2050s climate (red)

Figure 8-3 shows the annual average variability of the 2010 levelised costs with a 2080s medium emissions climate. There is a shift towards lower cost for Solar PV and a shift of increased costs for the others. It is difficult to see but the 2080s bars also indicate slightly more uncertainty.

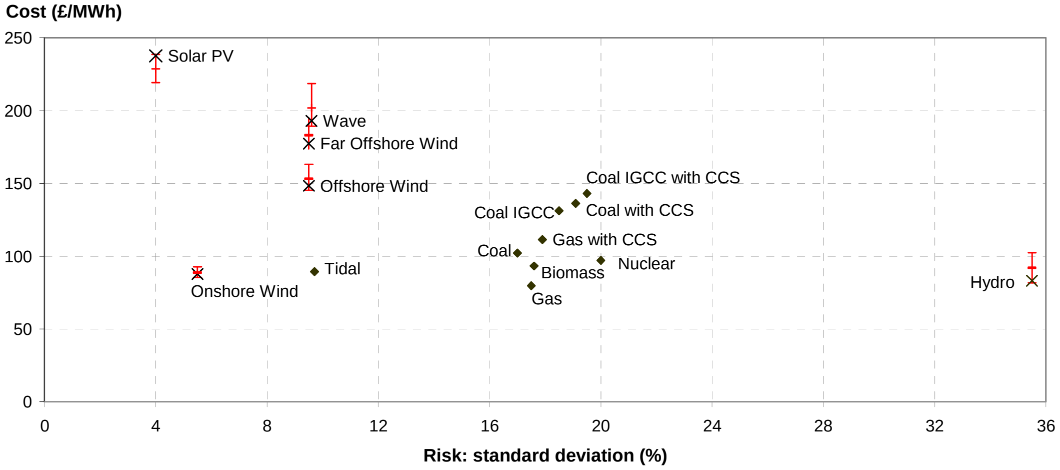


Figure 8-3: Cost Risk Graph for 2010 Cost Projections with baseline and 2080s climate

Figure 8-4 and Figure 8-5 show the same as shown previously but with the 2020 projected costs with baseline climate, 2050s and 2080s climate respectively. There are substantial cost reductions seen for solar PV, wave and wind technologies. However, the spread and risk values remain very similar.

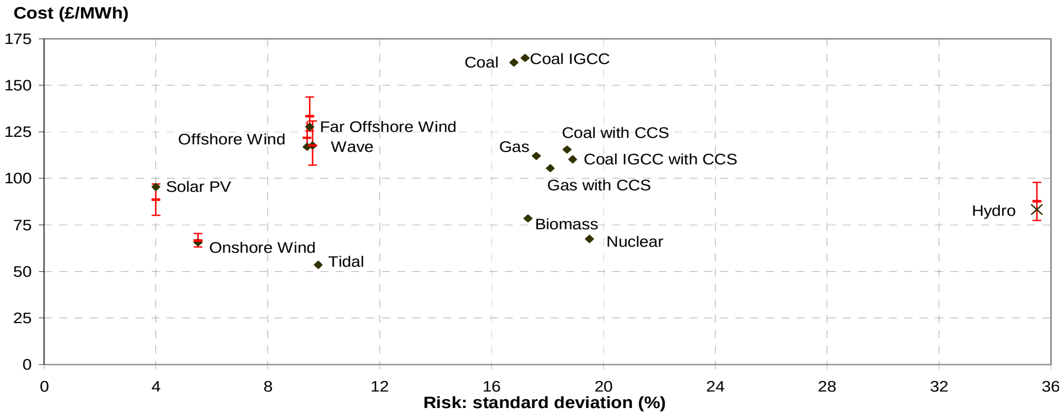


Figure 8-4: Cost Risk Graph for 2020 Cost Projections with baseline and 2050s climate

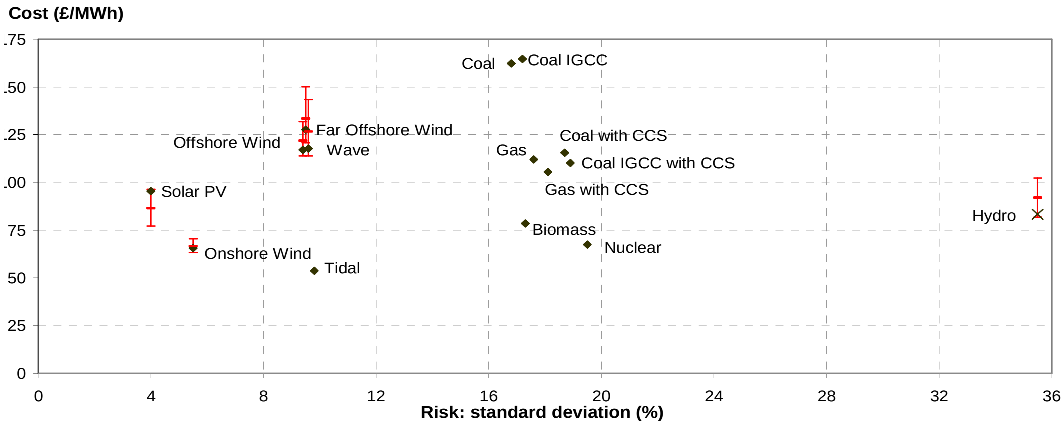


Figure 8-5: Cost Risk Graph for 2020 Cost Projections with baseline and 2080s climate

The values shown for the 2010 cost projections in Figure 8-2 and Figure 8-3, and 2020 cost projections in Figure 8-4 and Figure 8-5, are shown in Table 8-5 and Table 8-6 respectively.

2010 Levelised Cost Variability (£/MWh)						
Climate Scenario	Onshore Wind	Offshore Wind	Far Offshore Wind	Hydro	Wave	Solar PV
Baseline	**87.8**	**148.4**	**177.4**	**83.2**	**193.0**	**237.7**
2050 10%	91.7	159.9	191.1	97.9	211.5	239.2
2050 50%	**88.0**	**151.3**	**180.8**	**87.6**	**198.4**	**230.8**
2050 90%	85.0	144.6	172.9	77.4	187.8	222.4
2080 10%	92.6	163.2	195.1	104.0	218.6	238.7
2080 50%	**88.8**	**153.2**	**183.1**	**92.4**	**201.9**	**228.8**
2080 90%	85.4	145.3	173.7	79.2	189.2	219.4

Table 8-5: Climate cost variability for 2010 technology costs

2020 Levelised Cost Variability (£/MWh)						
Climate Scenario	Onshore Wind	Offshore Wind	Far Offshore Wind	Hydro	Wave	Solar PV
Baseline	**65.6**	**117.0**	**127.7**	**83.2**	**117.7**	**95.4**
2050 10%	69.5	128.5	141.4	97.9	136.2	96.9
2050 50%	**65.8**	**119.9**	**131.1**	**87.6**	**123.1**	**88.5**
2050 90%	62.8	113.2	123.2	77.4	112.5	80.1
2080 10%	70.4	131.8	145.4	104.0	143.3	96.4
2080 50%	**66.6**	**121.8**	**133.4**	**92.4**	**126.6**	**86.5**
2080 90%	63.2	113.9	124.0	79.2	113.9	77.1

Table 8-6: Climate cost variability for 2020 technology costs

It can be seen that that onshore and offshore wind, wave and hydro are all likely to see an increase in cost due to annual average climate variability; hydro and wave appear to be most affected. Solar PV costs look set to benefit from climate change with significant cost reduction for the 2050s and reducing even further for the 2080s.

8.3 Mean Variance Portfolio Theory Analysis for Baseline Climate

This section uses MVPT to explore several optimal mixes of electricity technology for the present and future time periods. All analyses and cost estimates are for the baseline climate. A set of 3 efficient frontiers are generated for the 2010 time period using projected 2010 costs and 3 sets of technology upper constraints. One efficient frontier is generated for the 2020 time period using 2020 projected costs and 2020 constraints. Two efficient frontiers are generated for the 2050s time period. The 2050s time period assumes the same technology costs as the 2020 costs. There are two sets of constraints used for the 2050s to give two alternative efficient frontiers.

Several optimal mix points on each of the efficient frontiers are chosen and discussed in more detail. They are compared with other optimal points on the efficient frontier and also compared with the actual 2009 mix. CO2 emissions for the different mixes are also explored and compared relative to 1990 CO_2 emission values.

8.3.1 Cost Projections for 2010 with Baseline Climate

This section MVPT analyses uses 2010 costs and risks for each technology. The first run uses 2010 tight constraints. The second run uses 2010 looser constraints. There are no constraints used in the final run. Figure 8-6 shows the generated MVPT efficient frontier curves using the three different constraint scenarios as shown in Table 8-4. Also shown for comparison are the estimated overall portfolio cost and risk values for the actual 2009 UK energy mix.

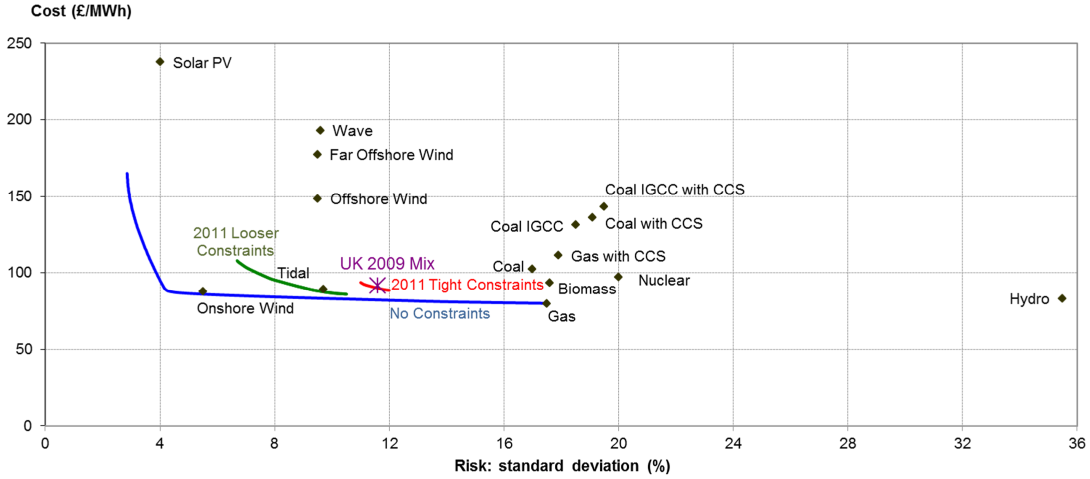


Figure 8-6: Portfolio Analysis for 2010 Cost Projections with baseline climate

8.3.1.1 A closer look at optimal mixes with 2010 'tight' constraints

Figure 8-7 zooms in specifically on the efficient frontier produced with the 2010 technology upper constraints. As mentioned, these constraints are bound very closely to the 2009 actual mix. It is demonstrated that despite limited room for manoeuvre there are more optimal mixes than the 2009 mix. Every point on the efficient frontier is an optimal mix.

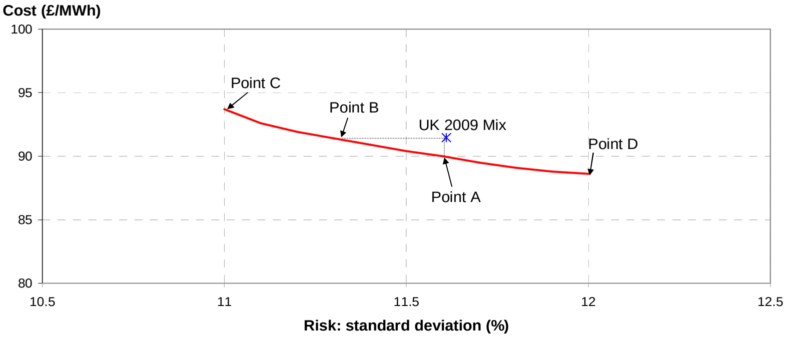


Figure 8-7: Four optimal portfolio mixes on the 2010 efficient frontier curve

The mix at Point A has the same risk value as 2009 but at a reduced cost. Point B has the same cost but a reduced risk. Points C and D both show optimal mixes at the extremes of the efficient frontier curve. Point C is sacrificing cost in order for minimal risk, while Point D is minimising risk at the expense of cost.

Table 8-7 provides details of the four highlighted optimal mix points on the efficient frontier. The assumed total energy output for 2010 is based on the 2009 output at roughly 372 TWh (DUKES 2010). Also shown are the CO_2 emissions for each mix and the percentage reduction relative to 1990 levels. The CO2 emissions are based on gas and coal emitting 405 and 915 Tonnes per GWh respectively and CCS technology being 90% efficient (DUKES 2010). Point D, which has relatively high proportions of gas, nuclear, and low proportions of coal, has the lowest emissions at 40.8% relative to 1990 emissions. There are probably other optimal mixes on the efficient frontier with lower emissions and this is explored for the 2020s, 2050s and 2080s time periods.

2010 Constraints - Annual Electrical Energy Output (TWh)					
	UK 2009	Point A	Point B	Point C	Point D
Gas	151.7	152.2	144.5	107.0	170.5
Coal	95.8	83.4	85.2	112.9	56.6
Nuclear	63.4	75.9	75.6	85.3	84.9
Onshore Wind	6.9	8.5	8.5	8.5	8.5
Offshore Wind	1.7	0.4	6.8	6.8	0
Hydro	4.8	6.8	6.8	6.8	6.8
Biomass	9.8	13.6	13.6	13.6	13.6
Wave	0	0	0	0	0
Tidal Stream	0	0	0	0	0
Solar PV	0	0	0	0	0
Cost (£/MWh)	91.5	90.0	91.4	93.7	88.6
Risk (%)	11.6	11.6	11.3	11.0	12.0
CO_2 (Million Tonnes)	149.1	138.0	136.4	146.6	120.9
CO_2 Reduction from 1990 (%)	26.9	32.4	33.1	28.1	40.8

Table 8-7: Details of mixes at Points A, B, C and D on the 2010 constraints efficient frontier

8.3.1.2 A closer look at optimal mixes with 2010 'looser' constraints

Figure 8-8 zooms in on the efficient frontier for the 2010 cost projections but bound by the 2010 'loose' technology constraint values. Point A has the same cost as the 2009 mix but with a 20% reduction in risk. Points B and C are optimal mixes close to the extremes of the efficient frontier: Point B sacrificing cost for lower risk and point C focussing on minimal optimal cost at the expense of increased risk. However, in all cases the risk is still reduced relative to the 2009 value.

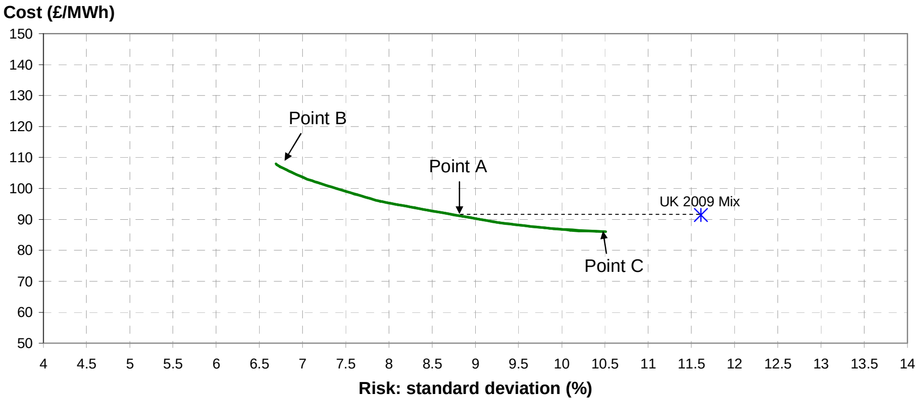


Figure 8-8: Three optimal portfolio mixes on the 2010 efficient frontier curve with looser constraints

Table 8-8 provides details of the three highlighted optimal mix points on Figure 8-8. Point A which has the same portfolio cost as 2009 but much reduced risk has achieved this by reducing roughly a third of energy supplied by gas and coal and replacing it with substantial increases in onshore wind, offshore wind, tidal stream, hydro and biomass; this has also dramatically reduced CO_2 emissions to 50% of 1990 levels.

Point B, which focuses on minimal risk, reduces gas even further and replaces it with more offshore wind and introduces significant amounts of three relatively more expensive, low risk technologies: far offshore wind, wave and solar. The CO_2 emissions are an improved reduction of 58.7% from 1990 levels.

Point C, focusing on minimal cost at the expense of risk, almost completely eliminates coal and replaces it with some gas, onshore wind, biomass, tidal stream and hydro. No offshore wind or solar feature in this mix due to their high costs. As a result of almost no coal the CO_2 emissions for this mix reduce even further than the mix at point B to a 65.9% reduction from 1990 levels.

All points on the efficient frontier curve have at least 48% CO_2 reduction, relative to 1990 levels, due to the relaxed constraint on renewable technologies. The lowest CO_2 level on the curve is at Point C, where coal is at its lowest level of 0.5 TWh.

2010 with looser Constraints - Annual Electrical Energy Output (TWh)				
	UK 2009	Point A	Point B	Point C
Gas (TWh)	151.7	111.8	60.2	170.5
Coal (TWh)	95.8	62.1	65.4	0.5
Nuclear (TWh)	63.4	54.5	46.6	69.4
Onshore Wind (TWh)	6.9	40.9	40.9	40.9
Offshore Wind (TWh)	1.7	12.0	34.1	0
Far Offshore Wind (TWh)	0	0	17.1	0
Hydro (TWh)	4.8	17.1	17.1	17.1
Biomass (TWh)	9.8	34.1	34.1	34.1
Wave (TWh)	0	0	8.5	0
Tidal Stream (TWh)	0	8.5	8.5	8.5
Solar PV (TWh)	0	0	8.5	0
Cost (£/MWh)	91.5	91.7	107.7	86.0
Risk (%)	11.6	8.7	6.7	10.5
CO_2 (Million Tonnes)	149.1	102.1	84.2	69.5
CO_2 Reduction from 1990 (%)	26.9	50.0	58.7	65.9

Table 8-8: Details of mixes at Points A, B and C on the 2010 more open constraints efficient frontier

8.3.1.3 A closer look at optimal mixes with no constraints

It is of interest to explore optimal mixes with no constraints but as mentioned in section 2.5.1 it is not truly practical as MVPT does not take into account any physical restrictions on individual technologies or their fuel source. Figure 8-9 shows the efficient frontier with no constraints.

Point C which is achieving minimal risk at the expense of cost is very interesting as this point shows very clearly Markowitz's MVPT theory of grouping assets with diversified risk characteristics together to reduce overall risk. The risk at point C is significantly less than the risk of any of the individual technologies. If the technologies were not diverse then the lowest risk possible would be the risk value of the lowest risk technology which is Solar PV. All points along the efficient frontier benefit in this way, it is just that the benefit is clearly seen in graphical form for any point on the efficient frontier that has a risk value less than any of the individual technologies. The details of the four optimal mix points on the efficient frontier in Figure 8-9 are shown in Table 8-9.

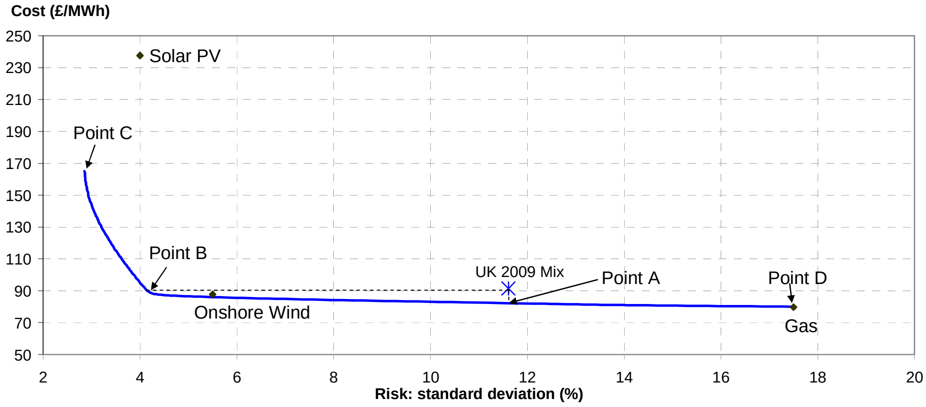


Figure 8-9: Three optimal portfolio mixes on the 2010 efficient frontier curve with looser constraints

Point A which has the same risk as the 2009 mix has reduced cost by 6.7 £/MWh by substantially increasing gas, onshore wind and hydro. There is no coal, biomass, nuclear, offshore wind, tidal stream, wave or solar PV in the mix. The CO_2 is reduced to 56% of 1990 levels.

Point B, which has the same cost as the 2009 mix has reduced risk by 7.6 percentage points which in real terms is a risk reduction of roughly 60%. This has been achieved by the mix being dominated by onshore wind, tidal stream resource and very low proportions of all other technologies. CO_2 levels are dramatically reduced to 89.4% of 1990 levels.

As previously discussed, Point C is the point of the efficient frontier with the lowest risk of 2.9%. Not surprisingly the dominant technology is Solar PV as it is the technology with the lowest risk; but by adding a significant proportion of onshore wind, another low risk technology, and small amounts of other diverse technologies, the risk is even further reduced to 2.9%. The high proportion of solar PV and other renewables also results in Point C having the greatest CO_2 reductions.

Point D is the lowest cost mix on the efficient frontier which is 100% of the technology with the lowest cost, in this case it is Gas. The trade-off is that there is high risk at 17.5%. This is the outcome of having no diversity in the mix.

2010 with No Constraints - Annual Electrical Energy Output (TWh)					
	UK 2009	Point A	Point B	Point C	Point D
Gas (TWh)	*151.7*	219.4	18.4	8.1	341
Coal (TWh)	*95.8*	0	15.6	12.3	0
Nuclear (TWh)	*63.4*	0	10	5.2	0
Onshore Wind (TWh)	*6.9*	90.5	204.4	103.3	0
Offshore Wind (TWh)	*1.7*	0	0.1	20.9	0
Far Offshore Wind (TWh)	*0*	0	0	0	0
Hydro (TWh)	*4.8*	31.2	4.2	1.5	0
Biomass (TWh)	*9.8*	0	23.9	12.8	0
Wave (TWh)	*0*	0	0	0	0
Tidal Stream (TWh)	*0*	0	64.4	35.8	0
Solar PV (TWh)	*0*	0	0	141.1	0
Cost (£/MWh)	*91.5*	82.2	88.9	154.4	79.7
Risk (%)	*11.6*	11.8	4.2	2.9	17.5
CO2 (Million Tonnes)	*149.1*	88.9	21.7	14.5	138.1
CO2 Reduction from 1990 (%)	*26.9*	56.4	89.4	92.9	32.3

Table 8-9: Details of mixes at Points A, B, C and D on the 2010 no constraints efficient frontier

8.3.2 Cost Projections for 2020 and 2050s with Baseline Climate

The aim of this section is to use MVPT to explore efficient portfolio mix options for 2020 by using 2020 projected costs and 2020 constraints. The 2050s time period is also explored by assuming technology costs are identical to the 2020 costs but adjusting constraints to values more applicable for the 2050s. The reason for doing this is due to the increasing uncertainty associated with attempting to project technology costs further into the future. There is very limited literature on cost projections for the 2050s and it is considered a more straightforward alternative to assume all technologies by 2020 have reached maturity and relative costs leading up to 2050 stay the same. There are two efficient frontiers explored for the 2050s using two different sets of 2050 constraints.

Shown in Figure 8-10 are the individual technology cost projections for the 2020s along with three efficient frontier portfolio curves which have been generated using the cost projections and three different technology constraint scenarios (2020s, 2050s and 2050s with 20%) as described earlier and with values shown in Table 8-4.

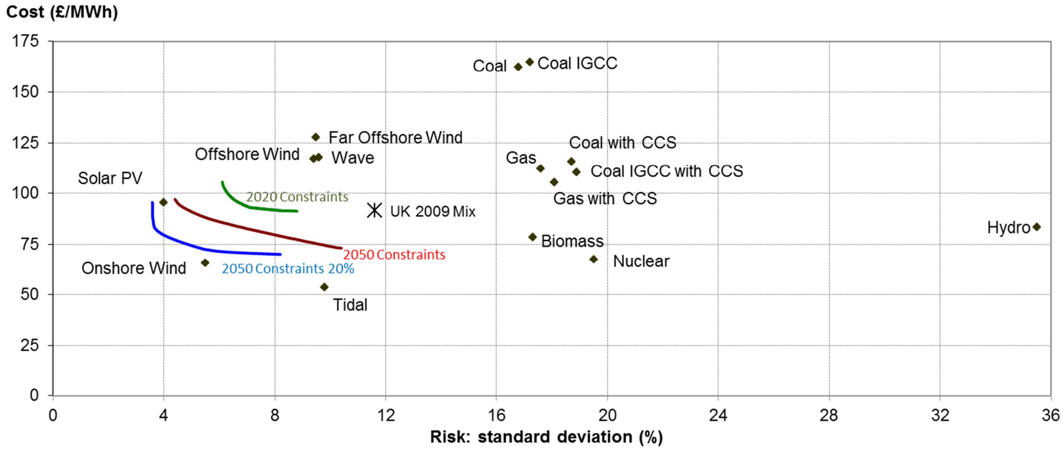


Figure 8-10: Portfolio Analysis for 2020 Cost Projections with baseline climate

8.3.2.1 Analysis with 2020 Constraints

Three optimal mix points on the ‘2020s constraints’ efficient frontier curve are highlighted in Figure 8-11, the mix details of each point are shown in Table 8-10.

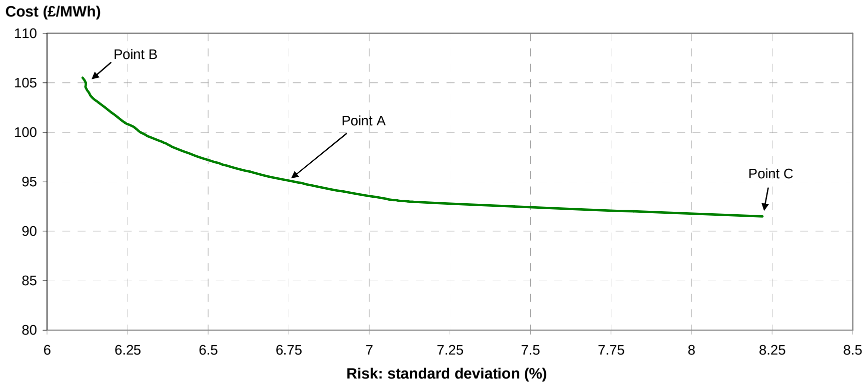


Figure 8-11: Three optimal portfolio mixes on the 2020 constraints efficient frontier

2020 Costs with 2020 Constraints - Annual Electrical Energy Output (TWh)				
	2020 Upper Constraint	Point A	Point B	Point C
Gas (TWh)	156	82.8	58.1	133
Gas with CCS (TWh)	4	0	0	4
Coal (TWh)	136	15.2	73.2	0
Coal with CCS (TWh)	4	4	0	4
Nuclear (TWh)	80	80	51.3	80
Onshore Wind (TWh)	48	48	48	48
Offshore Wind (TWh)	40	40	40	40
Far Offshore Wind (TWh)	40	40	40	1
Hydro (TWh)	20	20	19.5	20
Biomass (TWh)	40	40	40	40
Wave (TWh)	10	10	10	10
Tidal Stream (TWh)	10	10	10	10
Solar PV (TWh)	10	10	10	10
Cost (£/MWh)	-	95	105.5	91.5
Risk (%)	-	6.8	6.1	8.2
CO_2 (Million Tonnes)	-	47.8	90.5	54.4
CO_2 Reduction from 1990 (%)	-	76.6	55.7	73.3

Table 8-10: Points A, B and C on the 2020 costs with 2020 constraints efficient frontier

It is assumed that electricity generation has increased to 400 TWh per annum by 2020. As can be seen, all renewables are either at their maximum constraint or close to it in the mix at all three points on the efficient frontier. The 2020 cost projections assume they have reached or nearing maturity and costs are more competitive with fossil fuelled technologies, which also have projected CO_2 emission overheads and fuel price variability in the Mott MacDonald cost projections (Refer to Table 7-13).

Point A on the efficient frontier has just been shown as a midpoint on the curve, not too costly or risky. All renewables and nuclear are generating at their maximum constraint values. Gas generates a large proportion. Coal and Coal CCS generated the small remaining proportion. The CO_2 levels are a 76.6% reduction from 1990 levels.

Point B is aiming for minimal risk at the expense of cost. Renewables are at maximum levels but relative to Point A there is much more generation from coal at the expense of a large proportion of gas and nuclear.

Point C is aiming for minimal cost at the expense of risk. Gas, nuclear and renewable technologies make up the majority of the mix. Far offshore wind is minimal though due to its high cost. Coal use is greatly reduced and only CCS is in the mix.

To better illustrate the full range of efficient electricity generation mixes for 2020 costs with 2020 restraints, Figure 8-12 and Figure 8-13 show the generation mix and CO_2 emission values at all points on the efficient frontier. It was attempted to combine both graphs in one three dimensional graph but with unsatisfactory results; hence the two separate graphs show the same efficient mix options relative to cost and risk respectively. To better understand the figures also follow the 2020 efficient frontier shown in Figure 8-11. In essence these can be viewed as portfolio 'elevation' taken from either the cost plane or risk plane and showing mix and CO_2. In Figure 8-12, as the cost decreases, coal decreases, gas and nuclear increase; far offshore wind tails off at the lowest cost. In Figure 8-13, as the risk decreases, coal increases and gas decreases; far offshore wind and wave both tail off as the risk increases.

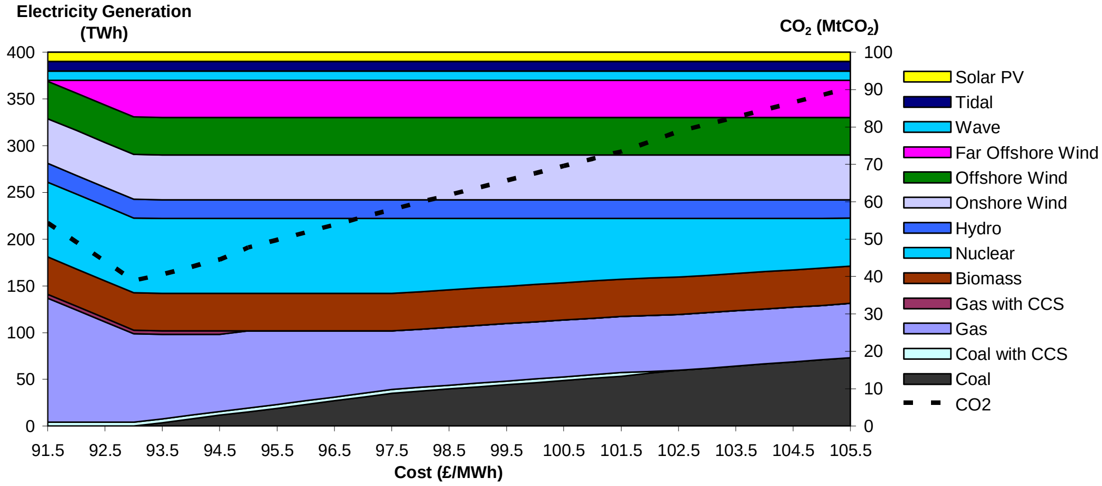


Figure 8-12: 2020 Efficient Frontier mix and CO_2 with respect to cost

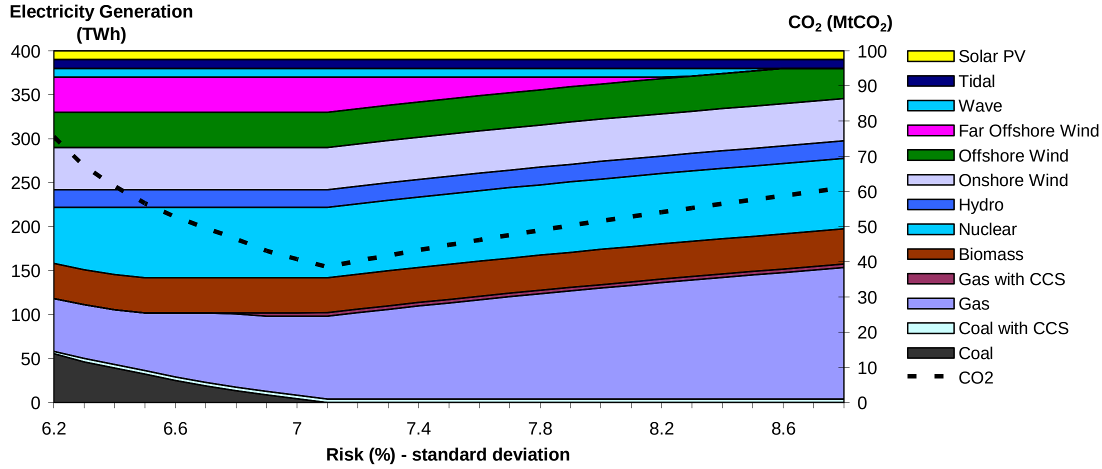


Figure 8-13: 2020 Efficient Frontier mix and CO_2 with respect to risk

There is literally a 3-way trade-off between risk, cost and CO_2. It is quite evident from looking at both the cost and risk figures how much the CO_2 output is related to the proportion of coal and gas in the mix. It can also be seen that a potentially better mix than points A, B and C would be where CO_2 is minimal. At this point cost is around 93 £/MWh and resulting risk is roughly 7.1%. This point on the efficient frontier (see Figure 8-11) would be approximately one third of the way towards Point C from Point A.

8.3.2.2 Analysis with 2050 Constraints

The 2050 constraints efficient frontier with three chosen optimal mix points is shown in Figure 8-14 and further mix and CO_2 information on the mixes are shown in Table 8-11.

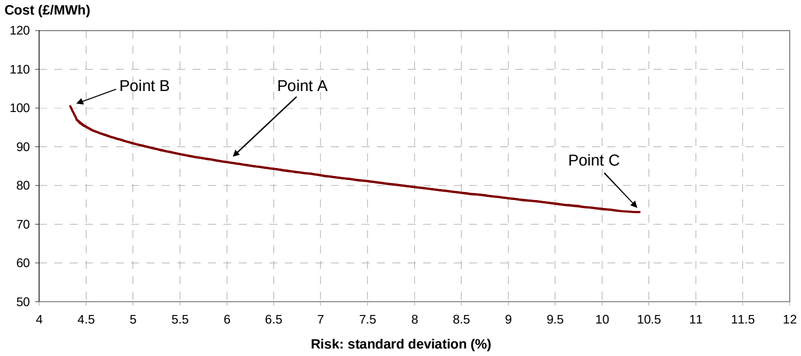


Figure 8-14: Three optimal portfolio mixes on the 2050 constraints efficient frontier

2020 Costs with 2050 Constraints - Annual Electrical Energy Output (TWh)				
	2050 Upper Constraint	Point A	Point B	Point C
Gas (TWh)	25	0	25	0
Gas with CCS (TWh)	150	17.5	6.6	27.8
Coal (TWh)	25	0	25	0
Coal with CCS (TWh)	150	11.5	13.6	0
Nuclear (TWh)	250	121.3	25.5	250
Onshore Wind (TWh)	75	75	75	75
Offshore Wind (TWh)	75	74.7	70.7	0
Far Offshore Wind (TWh)	75	0	75	0
Hydro (TWh)	25	25	8.5	25
Biomass (TWh)	50	50	50	50
Wave	50	50	50	0
Tidal Stream (TWh)	25	25	25	25
Solar PV (TWh)	50	50	50	47.2
Cost (£/MWh)	-	86	100.5	73.1
Risk (%)	-	6.0	4.3	10.4
CO_2 (Million Tonnes)	-	1.8	34.5	1.1
CO_2 Reduction from 1990 (%)	-	99.1	83.1	99.4

Table 8-11: Points A, B and C on the 2050 constraints efficient frontier

There are several large differences that arise from adjusting the portfolio constraints from values assumed for the 2020s to assumptions for the 2050s: the increased upper constraints of all renewables; the decreased upper constraints of coal and gas without CCS so as to ensure optimal portfolios have large CO_2 emission reductions; the increased upper constraints of coal and gas with CCS. In brief all points A, B and C have very little unabated coal or gas in the mix. Renewables are all at their maximum constraints, except at Point C which does not include far offshore wind. Nuclear has a large proportion in all especially Point C where low cost at the expense of risk is sought. It is assumed that electricity generation has increased further to 500 TWh by 2050.

Figure 8-15 and Figure 8-16 show the efficient frontier mix with respect to cost and risk respectively. What is very noticeable is the large proportion of nuclear in the low cost higher risk areas and it being replaced with far offshore wind, wave, and coal, Gas with CCS to a smaller extent, as the efficient frontier progresses towards higher cost lower risk optimal mixes. Also noticeable are the very low CO_2 emissions except for mixes in the extremes of low risk and high cost where coal and gas feature in the mix. In most cases it is 100% mitigated.

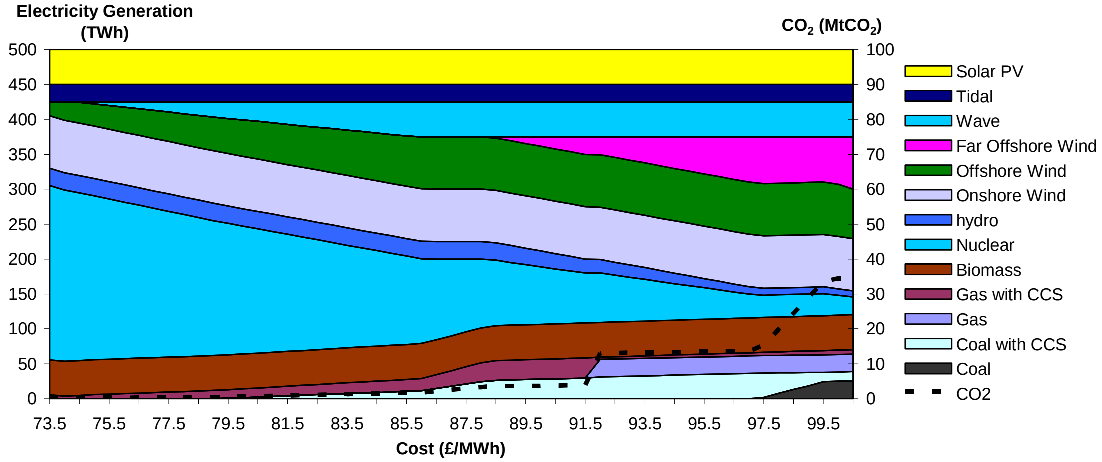


Figure 8-15: 2050 Efficient Frontier mix and CO_2 with respect to cost

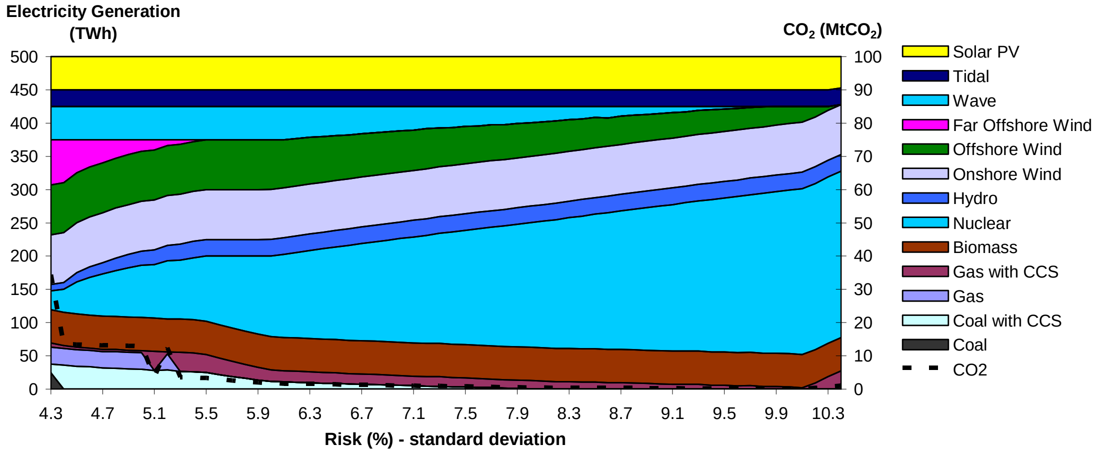


Figure 8-16: 2050 Efficient Frontier mix and CO_2 with respect to risk

8.3.2.3 Analysis with 2050 20% Constraints

There are many possible future outcomes and the constraints in this section are to give an alternative scenario to the 2050 constraints used previously in section 8.3.2.2. The aim of the choice of the ‘20%’ constraints are to prevent any technology dominating the mix and so to ensure there is even more diversity relative to the previous 2050 constraints. The majority of technologies are limited to a maximum of 20% of total generation; non CCS coal and gas are limited to 5% to ensure low CO_2 emissions. The efficient frontier for the 2050 20% constraints is shown in Figure 8-17, also highlighted are three points on the frontier. The details of the optimal mixes at those points are shown in Table 8-12.

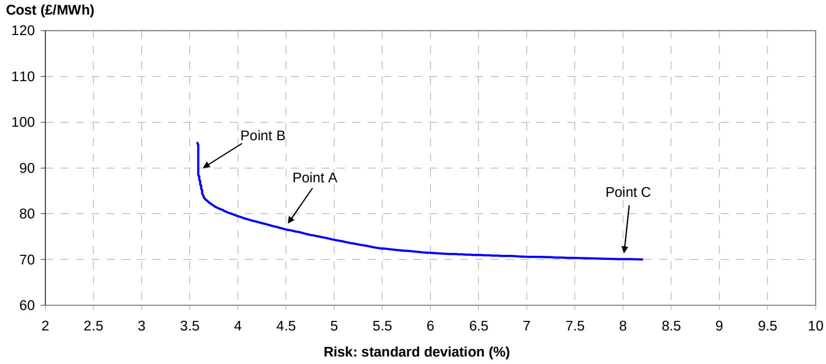


Figure 8-17: Three optimal portfolio mixes on the 2050 20% constraints efficient frontier

2020 Costs with 2050 20% Constraints - Annual Electrical Energy Output (TWh)				
	Upper Constraint	Point A	Point B	Point C
Gas (TWh)	25	0	24.1	0
Gas with CCS (TWh)	100	16.4	0	0
Coal (TWh)	25	0	25	0
Coal with CCS (TWh)	100	7.5	2.9	0
Nuclear (TWh)	100	62	17.4	100
Onshore Wind (TWh)	100	100	100	100
Offshore Wind (TWh)	100	27	0	0
Far Offshore Wind (TWh)	100	0	91.2	0
Hydro (TWh)	100	16	5.4	82
Biomass (TWh)	100	71.2	37.1	100
Wave	100	0	6.8	0
Tidal Stream (TWh)	100	100	90.1	100
Solar PV (TWh)	100	100	100	18
Cost (£/MWh)	-	76.6	90	70.1
Risk (%)	-	4.5	3.6	8
CO_2 (Million Tonnes)	-	1.3	32.9	0
CO_2 Reduction from 1990 (%)	-	99.3	83.9	100

Table 8-12: Points A, B and C on the 2050 20% constraints efficient frontier

The efficient frontier and optimal mixes using the 2050 20% constraints are significantly improved from those in section 8.3.2.2 for the 2050 constraints; this can be seen in Figure 8-10 as well as by comparing Table 8-11 and Table 8-12. The main reason for the improvement is that renewables, which benefit from being more economically competitive in the 2020s cost projections, have an increased higher proportional limit; whereas there are tighter constraints around nuclear. Coal and gas with CCS also have tighter constraints but are not constrained by the limits at any point along the efficient frontier.

Figure 8-18 and Figure 8-19 illustrate the mix along the efficient frontier curve from a cost and risk perspective respectively; it may be of use to also follow the curve (Figure 8-17) while studying them. In Figure 8-18, as the cost reduces, hydro and nuclear increase, offshore wind increases; far offshore and wave are in the mix only when the cost is high. In Figure 8-19, as the risk reduces, solar PV and offshore wind increases. When the risk is approaching its lowest value, hydro, nuclear tail off and gas and coal with CCS enter into the mix. It is quite obvious that the mixes of technologies are more evenly spread than in the 2050s mix (Figure 8-15 and Figure 8-16) especially with nuclear being reduced and renewables being increased to have an upper constraint of 20% of the overall mix.

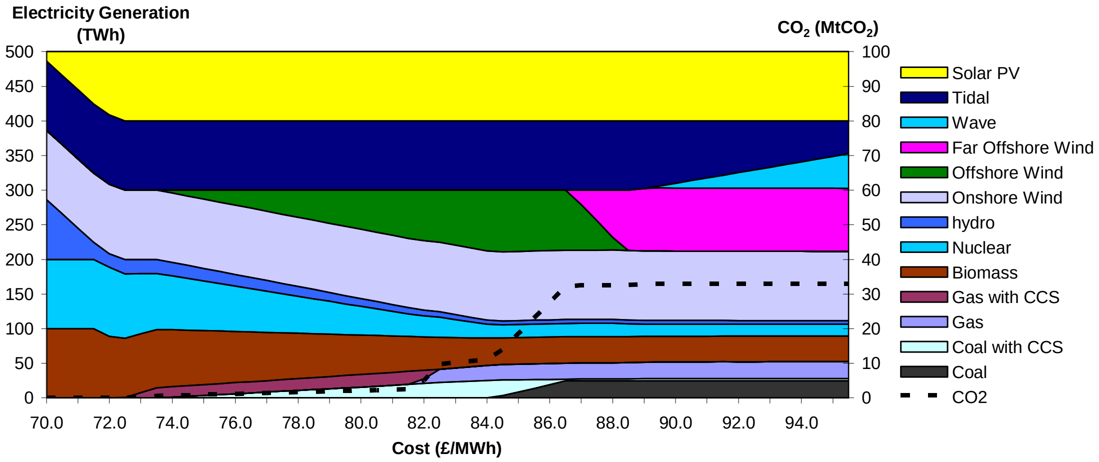


Figure 8-18: 2050 20% Efficient Frontier mix and CO$_2$ with respect to cost

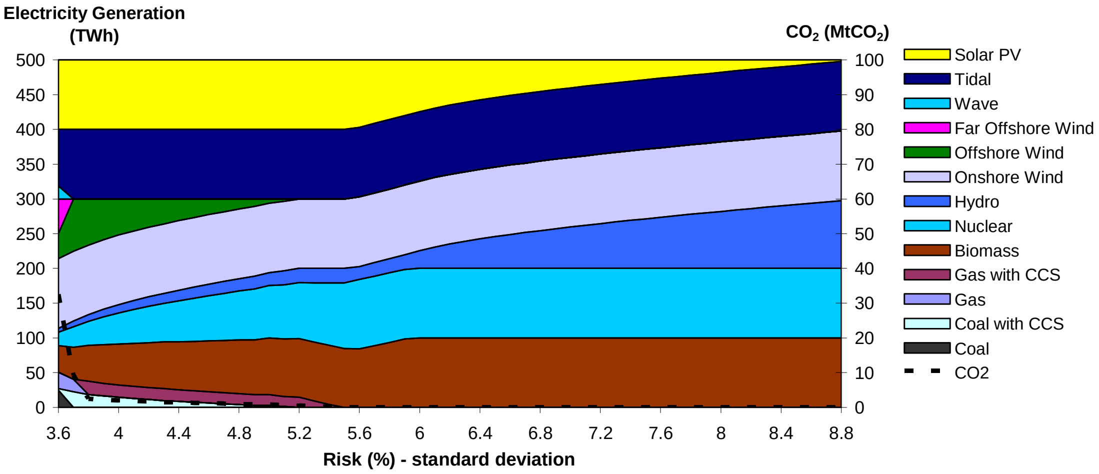


Figure 8-19: 2050 20% Efficient Frontier mix and CO$_2$ with respect to risk

8.3.3 Section Summary

This section has demonstrated the application of MVPT to generate efficient frontiers and choices of optimal mixes with each having their own characteristics. The sensitivity of MVPT to levelised costs, risks, and the constraints, has been shown, so too has the importance in choosing suitable technology constraint values. Also discussed are the choices of optimal mix to suit requirements such as cost of electricity, level of risk, and the level of CO_2 emissions. The baseline climate has been assumed stationary throughout the different time periods. The next section will investigate the sensitivity of MVPT to climate change.

8.4 Climate Change Impact

This section introduces the impact of annual average climate variability into the MVPT analyses. It uses the outcome of all previous chapters and aims to explore the impact that climate change and the resultant effect on individual technologies has on MVPT output and potential optimal mixes on the efficient frontier using the 2020s and 2050s technology costs and constraints, and comparing MVPT output for the 2050s and 2080s climate, with output for the baseline climate.

8.4.1 Sensitivity of MVPT curve for 2020s costs with 2020s constraints

This section uses MVPT to explore 2020 costs for the baseline, 2050s and 2080s climates. Shown in Figure 8-20 is the 2020s efficient frontier for the cost projections with 2020 technology constraints. The green line is the baseline climate (section 8.3.2.1). Shown in solid orange is the efficient frontier generated when using the resource output values for a 2050s medium emissions climate with 50% probability level; shown in the broken orange lines are the efficient frontiers generated using the 10% and 90% probability levels for the 2050s. The solid and broken blue lines represent the 2080s climate.

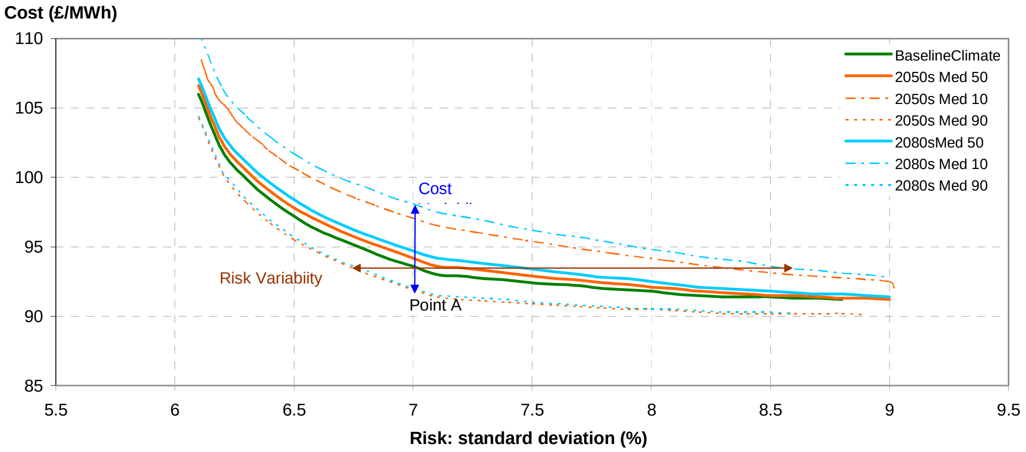


Figure 8-20: Efficient Frontier for 2020s constraints, 2020 costs, and 2050s & 2080s climate.

Overall, there are shifts in costs upwards and some increase in risk. This applies not only to the 50% climate probability but also the range, particularly so on the higher cost side. As can be seen there is substantial cost and risk sensitivity which both vary in sensitivity depending on the point on the efficient frontier and the resulting mix of technologies at that point. To explore further the variability of the cost, risk and mix at point A is investigated. Table 8-13 shows the cost variability (maintaining baseline risk) and risk variability (maintaining baseline cost) at Point A for the 2050s and 2080s climates.

Cost changes to optimal mix at 'Point A' - keeping risk stationary	
Climate	Cost Variability (£/MWh)
Baseline Climate	93.5
2050s Medium Emissions 50% (10%, 90%)	94.2 (97.1, 91.9)
2080s Medium Emissions 50% (10%, 90%)	94.7 (98.1, 92.0)
Risk changes to optimal mix at 'Point A' - keeping cost stationary	
	Risk Variability (% points)
Baseline Climate	7.0
2050s Medium Emissions 50% (10%, 90%)	7.2 (8.3, 6.7)
2080s Medium Emissions 50% (10%, 90%)	7.4 (8.6, 6.8)

Table 8-13: Portfolio cost and risk sensitivity

The 50% probability levels for the 2050s and 2080s increase in cost by 0.7 and 1.2 £/MWh respectively. The cost uncertainty between the 10% and 90% probability points are relatively large at 5.6 and 6.1 £/MWh respectively.

The portfolio risk increases slightly by 0.2% and 0.4% points for both future climates at the 50% probability level. The variability of risk between the 10% and 90% probability levels are 1.6 and 1.8 percentage points respectively for the 2050s and 2080s climates.

If the climate changes the energy output and cost of electricity will be affected. Technologies that use climate sensitive resource will change and in response the portfolio cost will change. The portfolio risk may be affected too, but to a lower extent. If the overall portfolio cost is to stay at the same level after any climate change then the mix will need to alter, which will alter the expected risk.

Table 8-14 shows the changes in mix required to maintain an optimal mix at the same overall cost over different climate change scenarios. It is the more expensive of the renewables, far offshore wind and wave, and coal that reduce. Gas and gas with CCS, increase to maintain the overall cost. The mixes for the lower 10% probability levels also generate more CO_2 and increase overall portfolio risk. For the 2050s and 2080s at 50% probability level the overall risk increases from the 7.0% baseline level, to 7.2% and 7.4% respectively. $C0_2$ emissions reduce slightly for the 2050s due to coal being replaced with gas. However, by the 2080s, gas has increased further to displace some far offshore wind, this results in a slight increase of CO_2 emission levels relative to baseline levels.

	Baseline	**2050 50%**	2050 10%	2050 90%	**2080 50%**	2080 10%	2080 90%
Gas (TWh)	**112.2**	**121.3**	169.1	101.8	**133.8**	178.4	103.4
Gas with CCS (TWh)	**5.0**	**5.0**	5.0	0	**5.0**	5.0	0
Coal	**5.3**	**0**	0	20.7	**0**	0	19.1
Coal with CCS (TWh)	**5.0**	**5.0**	5.0	5.0	**5.0**	5.0	5.0
Nuclear (TWh)	**100**	**100**	100	100	**100**	100	100
Onshore Wind (TWh)	**60**	**60**	60	60	**60**	60	60
Offshore Wind (TWh)	**50**	**50**	50	50	**50**	50	50
Far Offshore Wind (TWh)	**50**	**46.2**	0	50	**33.7**	0	50
Hydro (TWh)	**25**	**25**	25	25	**25**	25	25
Biomass (TWh)	**50**	**50**	50	50	**50**	50	50
Wave (TWh)	**12.5**	**12.5**	10.9	12.5	**12.5**	1.6	12.5
Tidal Stream (TWh)	**12.5**	**12.5**	12.5	12.5	**12.5**	12.5	12.5
Solar PV (TWh)	**12.5**	**12.5**	12.5	12.5	**12.5**	12.5	12.5
Cost (£/MWh)	**93.5**	**93.5**	93.5	93.5	**93.5**	93.5	93.5
Risk (%)	**7.0**	**7.2**	8.3	6.7	**7.4**	8.6	6.8
CO_2 (Million Tonnes)	**51.0**	**49.8**	69.1	60.6	**54.9**	72.9	59.8
CO_2 Reduction from 1990 (%)	**75.0**	**75.6**	66.1	70.3	**73.1**	64.3	70.7

Table 8-14: Optimal mix change at 'Point A' to maintain overall cost at baseline climate value

As mentioned the risk stays largely constant if the mix does not change. Table 8-15 shows the changes in cost in order to maintain the same overall expected portfolio risk at the baseline value. The changes in proportion of the mix and CO_2 emissions were negligible and not shown. It shows a cost change of 0.7% (3.9%, -1.7%) for the 2050s and 1.3% (4.9%, -1.6%) for the 2080s.

	Baseline	2050 50%	2050 10%	2050 90%	2080 50%	2080 10%	2080 90%
Cost (£/MWh)	93.5	94.2	97.1	91.9	94.7	98.1	92.0
Risk (%)	7.0	7.0	7.0	7.0	7.0	7.0	7.0

Table 8-15: Optimal mix change at 'Point A' to maintain overall portfolio risk at baseline climate level

8.4.2 Sensitivity of MVPT curve for the 2050s

This section now repeats what was explored in section 8.4.1 using the wider 2050s constraints instead of the 2020s constraints. The efficient frontier curves for the different climates are shown in Figure 8-21. The cost and risk variability is shown for a mix at Point A. This has a much steeper curve than for the 2020s which is due to the reduced constraints on renewable technologies.

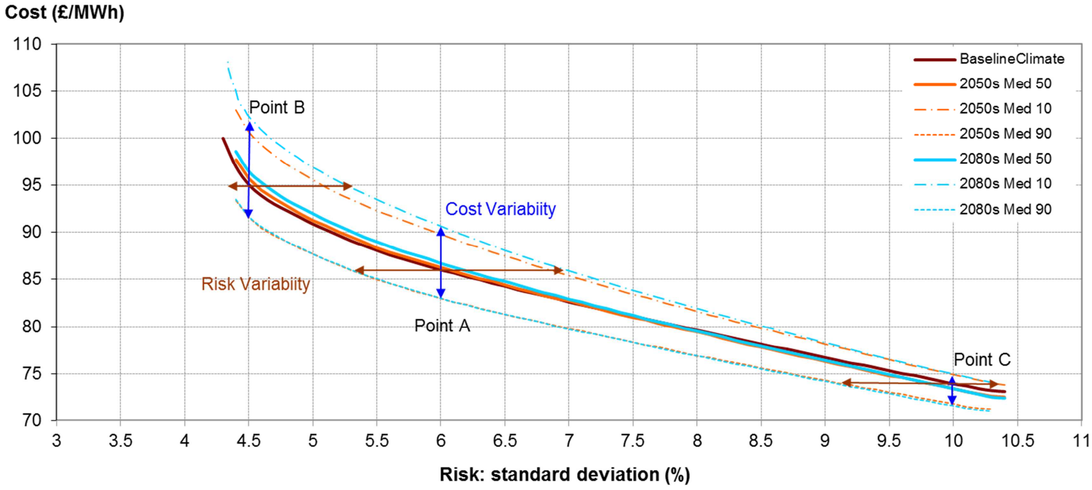


Figure 8-21: Efficient Frontier for 2050s constraints, 2020 costs, and 2080s climate.

When comparing the baseline curve with the 2050s and 2080s 50% probability curves it can be seen that they both cross the baseline curve at around £80/MWh (8% risk). This is occurring above 8% risk because solar PV resource improves in the future climates and both offshore wind and wave are starting to tail off. Solar PV has then enough resource in the mix to counterbalance the negative effects of the renewable technologies that have reduced output due to climate change. This implies that future electricity generation mixes with significant levels of Solar PV as part of the portfolio, will be more resilient to climate change.

Looking at how the optimal mix at Point A is affected by climate change, Table 8-16 shows the change in the overall cost to maintain a stationary portfolio risk and overall risk to maintain portfolio cost over the changing climates for Points A, B and C.

Portfolio Variability	Cost Variability (£/MWh)		
	Point A	Point B	Point C
Baseline Climate	86.0	95.1	73.9
2050s Medium Emissions 50% (10%, 90%)	86.3 (89.8, 83.0)	95.7 (100.7, 91.7)	73.9 (75.0, 71.6)
2080s Medium Emissions 50% (10%, 90%)	86.7 (90.7, 83.0)	96.5 (101.5, 91.7)	73.9 (75.0, 71.6)
	Risk Variability (% points)		
Baseline Climate	6.0	4.5	10.0
2050s Medium Emissions 50% (10%, 90%)	6.1 (6.9, 5.3)	4.6 (4.3, 5.1)	10.0 (9.1, 10.4)
2080s Medium Emissions 50% (10%, 90%)	6.2 (7.0, 5.3)	4.7 (4.3, 5.3)	10.0 (9.1, 10.4)

Table 8-16: Portfolio cost and risk sensitivity

Table 8-17 and Table 8-18 show the details of changes in mix necessary to keep overall cost and risk stationary respectively over changing climates for Point A. As can be seen it is the more expensive renewables (wave, far offshore wind and offshore wind) that reduce in proportion of mix slightly in the 2050s and 2080s altered climates with 50% probability, due to the reduction in wind resource. The reduction in renewables is replaced by increasing nuclear, coal with CCS and gas with CCS. Solar PV remains at its maximum extent.

	Baseline	2050 50%	2050 10%	2050 90%	2080 50%	2080 10%	2080 90%
Gas (TWh)	0	0	0	0	0	0	0
Gas with CCS (TWh)	17.5	22.6	33.3	25.6	25.7	36.5	26.1
Coal	0	0	0	0	0	0	0
Coal with CCS (TWh)	11.5	17.6	29.2	23.5	21.2	32.7	24.1
Nuclear (TWh)	121.3	121.8	140.7	90.6	124	142.8	90.5
Onshore Wind (TWh)	75	75	75	75	75	75	75
Offshore Wind (TWh)	74.7	75	71.9	75	75	63	75
Far Offshore Wind (TWh)	0	0	0	11.2	0	0	10.1
Hydro (TWh)	25	25	25	24.1	25	25	24.2
Biomass (TWh)	50	50	50	50	50	50	50
Wave (TWh)	50	38	0	50	29	0	50
Tidal Stream (TWh)	25	25	25	25	25	25	25
Solar PV (TWh)	50	50	50	50	50	50	50
Cost (£/MWh)	86	86.0	86.0	86.0	86	86	86
Risk (%)	6	6.1	6.9	5.3	6.2	7	5.3
CO_2 (Million Tonnes)	1.8	2.5	4	3.2	3	4.5	3.3
CO_2 Reduction from 1990 (%)	99.1	98.8	98.0	98.4	98.5	97.8	98.4

Table 8-17: Changes in overall cost to maintain baseline risk value for Point A

	Baseline	2050 50%	2050 10%	2050 90%	2080 50%	2080 10%	2080 90%
Gas (TWh)	0	0	0	0	0	0	0
Gas with CCS (TWh)	17.5	22.7	33.1	17.4	25.7	37.2	17.3
Coal	0	0	0	0	0	0	0
Coal with CCS (TWh)	11.5	17.9	30.9	11.3	22	36	11.4
Nuclear (TWh)	121.3	119.2	112.4	121.3	117.6	108.8	121.3
Onshore Wind (TWh)	75	75	75	75	75	75	75
Offshore Wind (TWh)	74.7	75	75	75	75	75	75
Far Offshore Wind (TWh)	0	0	0	0	0	0	0
Hydro (TWh)	25	25	25	25	25	25	25
Biomass (TWh)	50	50	50	50	50	50	50
Wave (TWh)	50	40.2	23.6	50	34.7	18	50
Tidal Stream (TWh)	25	25	25	25	25	25	25
Solar PV (TWh)	50	50	50	50	50	50	50
Cost (£/MWh)	86	86.3	89.8	83	86.7	90.7	83
Risk (%)	6	6	6	6	6	6	6
CO_2 (Million Tonnes)	1.8	2.6	4.2	1.7	3.1	4.8	1.7
CO_2 Reduction from 1990 (%)	99.1	98.7	98	99.1	98.5	97.6	99.1

Table 8-18: Changes in overall risk to maintain baseline cost value for Point A

8.4.3 Sensitivity of MVPT to climate change of individual technologies

In previous sections 8.4.1 and 8.4.2 the analysis explores the collective sensitivity of MVPT. The following sub-sections investigate the impact individual technologies affected by annual average climate variability have on optimal portfolio mixes. Three optimal mix points (Point A, B and C) on the efficient frontier are chosen for closer investigation of each technology.

8.4.3.1 Onshore Wind

Shown Figure 8-22 is the impact of onshore wind annual average variability for the 2080s climate on the efficient frontier. The input cost parameters are the 2020 cost projections and the constraints are the 2050 constraints.

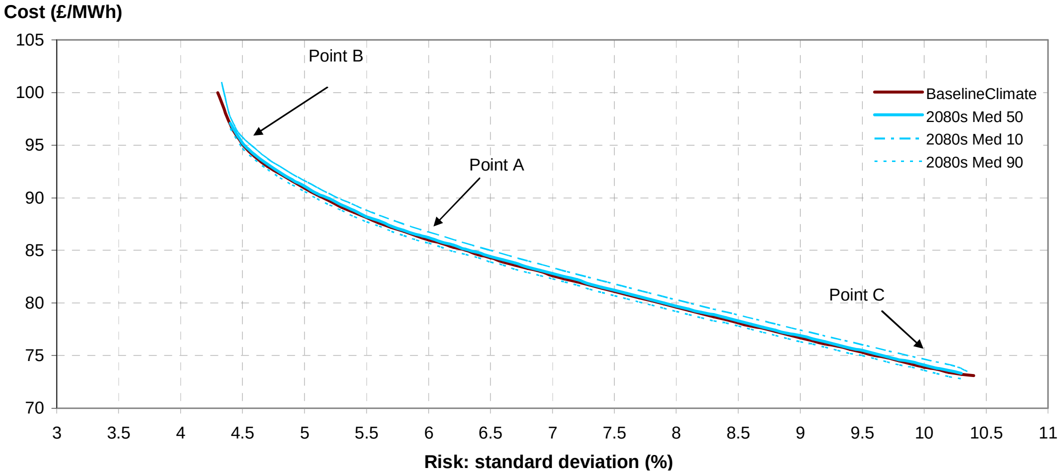


Figure 8-22: Impact of onshore wind annual average climate variability on optimal portfolio mixes

The 2050 constraints limit onshore wind to a maximum of 15% of the total energy mix and throughout all locations on the efficient frontier for baseline and the 2080s 50%, 10% and 90% the share of onshore wind is constant at its maximum constraint.

The variability of overall cost to keep the risk the same as the baseline and risk to maintain the same cost for the three points (A, B and C) are shown in Table 8-19. There are marginal changes to both cost and risk for the 50% probability level. However, there is a significant cost increase beyond point B, towards the low extreme of cost.

Onshore Wind Portfolio Variability	Cost Variability (£/MWh)		
	Point A	Point B	Point C
Baseline Climate	86.0	95.1	73.9
2080s Medium Emissions 50% (10%, 90%)	86.2 (86.7, 85.7)	95.2 (95.8, 94.7)	74.1 (74.7, 73.6)
	Risk Variability (% points)		
Baseline Climate	6.0	4.5	10.0
2080s Medium Emissions 50% (10%, 90%)	6.1 (6.2, 5.9)	4.6 (4.6, 4.5)	10.1 (10.3, 10.0)

Table 8-19: Portfolio cost and risk sensitivity – onshore wind

To maintain the same baseline cost by adjusting risk there are slight adjustments in the proportions of thermal plant technologies and offshore wind.

8.4.3.2 Offshore and Far Offshore Wind

The 2050 constraints limit both offshore and far offshore wind to a maximum of 15% of the total energy mix. The mix of offshore wind varies from none in the lower cost regions of the efficient frontier, to its maximum constraint in higher cost regions. In Figure 8-23 there is quite a noticeable change in the efficient frontier when the impact of only offshore wind annual average climate variability on optimal portfolios is investigated.

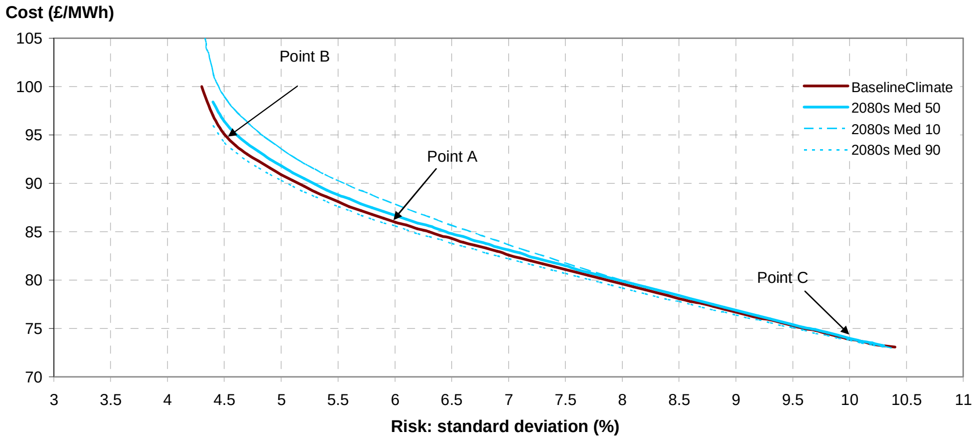


Figure 8-23: Impact of offshore wind annual average climate variability on optimal portfolio mixes

This is particularly noticeable in the higher cost, lower risk regions on the efficient frontiers. Risk increases as the portfolio cost increases. Table 8-20 shows the variability of cost to maintain risk and variability of risk to maintain overall cost value respectively when the efficient frontier and optimal mix is affected by the change in the future climate.

Offshore Wind Portfolio Variability	Cost Variability (£/MWh)		
	Point A	Point B	Point C
Baseline Climate	86.0	95.1	73.9
2080s Medium Emissions 50% (10%, 90%)	86.7 (87.9, 85.6)	96.4 (99.0, 94.2)	74.0 (74.0, 73.8)
	Risk Variability (% points)		
Baseline Climate	6.0	4.5	10.0
2080s Medium Emissions 50% (10%, 90%)	6.2 (6.4, 5.9)	4.6 (4.8, 4.4)	10.0 (10.0, 9.9)

Table 8-20: Portfolio cost and risk sensitivity – offshore wind

Offshore wind appears to be affected more by climate change than onshore wind, in terms of cost, risk and optimal fuel mixes, particularly in the higher cost regions.

Table 8-21 to Table 8-23 show the changes in mix required to maintain the same portfolio cost and risk, respectively for different climate scenarios at Point A, Point B and Point C respectively, on the efficient frontier shown in Figure 8-23.

Point A sees a marked reduction in the share of offshore wind for the 2080s climate at 50% probability level from a baseline of 74.7 TWh to 60.3 (37.4, 75.0) TWh in order to maintain the overall cost of £86.0/MWh, the reduction in offshore wind is replaced with coal and gas with CCS and nuclear, the overall risk increases from 6.0% to 6.2% (6.4%, 5.1%). Far offshore wind is not in the mix. The change required to maintain the overall risk at the baseline climate level (6.0%) for future climates is not quite as dramatic but still reduces offshore wind to 65.2 (51.4, 75.0) TWh. Nuclear reduces also. Coal and gas with CCS increase to cover the shortfall. The overall cost increases from £86.0/MWh to £86.7 (£87.9, £85.6) / MWh. CO_2 remains very low.

		Stationary Cost			Stationary Risk		
	Baseline	2080s 50%	2080s 10%	2080s 90%	2080s 50%	2080s 10%	2080s 90%
Gas (TWh)	0	0	0	0	0	0	0
Gas with CCS (TWh)	17.5	22	31.3	19.5	22.7	31	17.3
Coal	0	0	0	0	0	0	0
Coal with CCS (TWh)	11.5	16.6	27.3	14.3	17.6	28.1	11.3
Nuclear (TWh)	121.3	126.1	129	116.3	119.4	114.6	121.3
Onshore Wind (TWh)	75	75	75	75	75	75	75
Offshore Wind (TWh)	74.7	60.3	37.4	75	65.2	51.4	75
Far Offshore Wind (TWh)	0	0	0	0	0	0	0
Hydro (TWh)	25	25	25	25	25	25	25
Biomass (TWh)	50	50	50	50	50	50	50
Wave (TWh)	50	50	50	50	50	50	50
Tidal Stream (TWh)	25	25	25	25	25	25	25
Solar PV (TWh)	50	50	50	50	50	50	50
Cost (£/MWh)	**86**	**86**	**86**	**86**	86.7	87.9	85.6
Risk (%)	**6.0**	6.2	6.4	5.9	**6.0**	**6.0**	**6.0**
CO_2 (Million Tonnes)	1.8	2.4	3.8	2.1	2.5	3.8	1.7
CO_2 Reduction from 1990 (%)	99.1	98.8	98.2	99	98.8	98.1	99.1

Table 8-21: Offshore Wind – Variability of optimal mix at point A

At Point B offshore wind is at its maximum constraint level for the baseline and 2080s 10%, 50% and 90% probability level projections. Far offshore wind is also in the mix at 49.5 TWh for the baseline climate, falling to 37.8 (18.0, 49.5) TWh in the 2080s to maintain the baseline overall cost and falling to 48.1 (45.9, 51.0) TWh to maintain the overall baseline risk. The energy deficit, when baseline cost is maintained (£95.0 / MWh), is replaced with nuclear, hydro and lesser amounts of coal and gas - both with CCS. For baseline risk value (4.5%) to be maintained the deficit is replaced with nuclear, coal and gas both with CCS. The overall cost increases from £95.1/MWh to £96.4 (£99.0, £94.2) / MWh.

		Stationary Cost			Stationary Risk		
	Baseline	2080s 50%	2080s 10%	2080s 90%	2080s 50%	2080s 10%	2080s 90%
Gas (TWh)	25	25	25	25	25	25	25
Gas with CCS (TWh)	4.1	5.2	8.7	3.6	5	6.7	3.2
Coal	0	0	0	0	0	0	0
Coal with CCS (TWh)	34.3	34.7	37.8	34.3	35.5	37.7	33.1
Nuclear (TWh)	48	56.1	65.9	42.7	47.4	45.8	48.7
Onshore Wind (TWh)	75	75	75	75	75	75	75
Offshore Wind (TWh)	75	75	75	75	75	75	75
Far Offshore Wind (TWh)	49.5	37.8	18	57	48.1	45.9	51.0
Hydro (TWh)	14	16.2	19.5	12.5	14	14	13.9
Biomass (TWh)	50	50	50	50	50	50	50
Wave (TWh)	50	50	50	50	50	50	50
Tidal Stream (TWh)	25	25	25	25	25	25	25
Solar PV (TWh)	50	50	50	50	50	50	50
Cost (£/MWh)	**95.1**	**95**	**95**	**95**	96.4	99	94.2
Risk (%)	**4.5**	4.6	4.8	4.5	**4.5**	**4.5**	**4.5**
CO_2 (Million Tonnes)	13.4	13.5	13.9	13.4	13.6	13.8	13.3
CO_2 Reduction from 1990 (%)	93.4	93.4	93.2	93.4	93.3	93.2	93.5

Table 8-22: Offshore Wind – Variability of optimal mix at point B

Point C is interesting as the baseline offshore mix has 25.7 TWh of offshore wind and no far offshore wind. The 2080s portfolio has 0 (0, 30.8) TWh of offshore wind to maintain cost and 0 (0, 28.2) TWh to maintain risk, at the baseline level. The deficit when cost is maintained is replaced largely with wave (21 TWh), which does not feature at all in the baseline mix. Gas with CCS is increased. Nuclear reduces slightly. When the baseline risk is maintained the deficit is replaced in a similar way as for maintaining cost. Cost and risk remain largely unchanged.

		Stationary Cost			Stationary Risk		
	Baseline	2080s 50%	2080s 10%	2080s 90%	2080s 50%	2080s 10%	2080s 90%
Gas (TWh)	0	0	0	0	0	0	0
Gas with CCS (TWh)	3.3	10	9.4	0	9.4	10	0
Coal	0	0	0	0	0	0	0
Coal with CCS (TWh)	0	0	0	0	0	0	0
Nuclear (TWh)	246	244.1	244.3	244.2	244.3	244.1	246.8
Onshore Wind (TWh)	75	75	75	75	75	75	75
Offshore Wind (TWh)	25.7	0	0	30.8	0	0	28.2
Far Offshore Wind (TWh)	0	0	0	0	0	0	0
Hydro (TWh)	25	25	25	25	25	25	25
Biomass (TWh)	50	50	50	50	50	50	50
Wave (TWh)	0	21	21.3	0	21.3	21	0
Tidal Stream (TWh)	25	25	25	25	25	25	25
Solar PV (TWh)	50	50	50	50	50	50	50
Cost (£/MWh)	**73.9**	**74**	**74**	**74**	74	74	73.8
Risk (%)	**10**	10	10	9.9	**10**	**10**	**10**
CO_2 (Million Tonnes)	0.1	0.4	0.4	0	0.4	0.4	0
CO_2 Reduction from 1990 (%)	99.9	99.8	99.8	100	99.8	99.8	100

Table 8-23: Offshore Wind – Variability of optimal mix at point C

8.4.3.3 Solar PV

Solar PV is limited to a maximum 10% of the total energy mix by the 2050 constraints. Shown in Figure 8-24 is the change in the 2050s efficient frontier due to different Solar PV resource climates. The Solar PV mix is at its maximum constraint at each of the three points and for each of the climate scenarios. It can be seen that the 2080s climate which has greater solar resource actually improves the efficient frontier quite significantly, even when the proportion of solar in the energy mix is constrained to 10%.

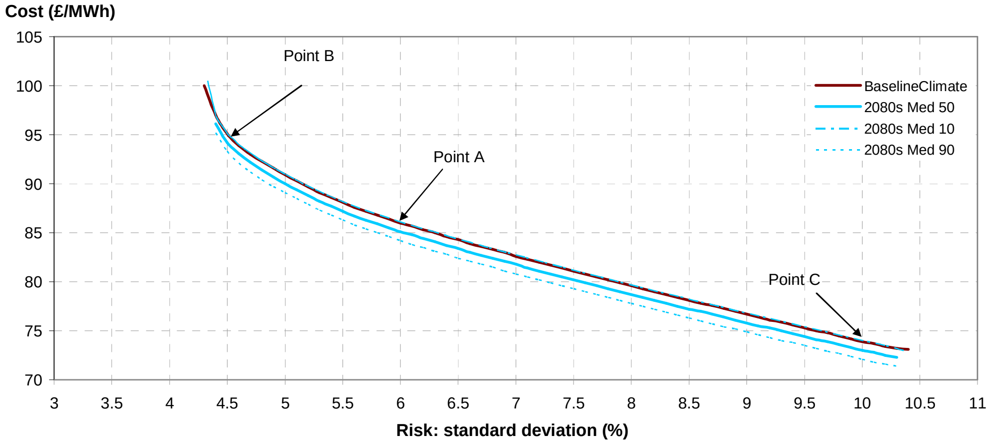


Figure 8-24: Impact of solar PV annual average climate variability on optimal portfolio mixes

The changes to overall cost and risk due to the different solar climate resources can be seen in Table 8-24. As can be seen there is a change in cost of -0.9 (0.1 -1.8) £/MWh at all three points. Risk reduces also, except at Point B where it is relatively stationary.

Solar PV Portfolio Variability	Cost Variability (£/MWh)		
	Point A	Point B	Point C
Baseline Climate	86.0	95.1	73.9
2080s Medium Emissions 50% (10%, 90%)	85.1 (86.1, 84.2)	94.2 (95.2, 93.3)	73.0 (74.0, 72.1)
	Risk Variability (% points)		
Baseline Climate	6.0	4.5	10.0
2080s Medium Emissions 50% (10%, 90%)	5.8 (6.0, 5.6)	4.5 (4.5, 4.4)	9.7 (10.0, 9.3)

Table 8-24: Portfolio cost and risk sensitivity – solar PV

The changes in mix required to maintain the overall cost and risk values at Points A, B and C are shown in Table 8-25, Table 8-26 and Table 8-27.

At Point A in maintaining the overall cost at the baseline level the overall risk changes by -0.2% points (0.0%, -0.4%), CO_2 emissions are reduced, this is achieved by slight changes to offshore wind gas and coal with CCS and nuclear. The mix in maintaining the overall risk at baseline levels stays stationary but changes the cost by -0.9 (+0.1, 01.8) £/MWh.

Technology		Stationary Cost			Stationary Risk		
	Baseline	2080s 50%	2080s 10%	2080s 90%	2080s 50%	2080s 10%	2080s 90%
Gas (TWh)	0	0	0	0	0	0	0
Gas with CCS (TWh)	17.5	21.5	17.3	26.1	17.5	17.5	17.5
Coal	0	0	0	0	0	0	0
Coal with CCS (TWh)	11.5	17.1	11.3	23.2	11.3	11.6	11.5
Nuclear (TWh)	121.3	111.4	122.6	100.7	121.3	121.3	121.3
Onshore Wind (TWh)	75	75	75	75	75	75	75
Offshore Wind (TWh)	74.7	75	73.9	75	75	74.6	74.7
Far Offshore Wind (TWh)	0	0	0	0	0	0	0
Hydro (TWh)	25	25	25	25	25	25	25
Biomass (TWh)	50	50	50	50	50	50	50
Wave (TWh)	50	50	50	50	50	50	50
Tidal Stream (TWh)	25	25	25	25	25	25	25
Solar PV (TWh)	50	50	50	50	50	50	50
Cost (£/MWh)	**86**	**86**	**86**	**86**	85.1	86.1	84.2
Risk (%)	**6.0**	5.8	6	5.6	**6.0**	**6.0**	**6.0**
CO_2 (Million Tonnes)	1.8	2.4	1.7	3.2	1.7	1.8	1.8
CO_2 Reduction from 1990 (%)	99.1	98.8	99.2	98.4	99.1	99.1	99.1

Table 8-25: Solar PV – Variability of optimal mix at point A

At Point B the change in mix to maintain the baseline cost and to maintain the baseline risk has minimal effect on the other. There are slight changes in proportion of coal and gas with CCS, nuclear, far offshore wind and hydro.

Technology		Stationary Cost			Stationary Risk		
	Baseline	2080s 50%	2080s 10%	2080s 90%	2080s 50%	2080s 10%	2080s 90%
Gas (TWh)	25	25	25	25	25	25	25
Gas with CCS (TWh)	4.1	4.2	3.9	4.4	3.8	3.9	4
Coal	0	0	0	0	0	0	0
Coal with CCS (TWh)	34.3	35.1	34	36	34.1	34.1	34.2
Nuclear (TWh)	48	42.3	49.5	35.4	48.3	48.3	48.1
Onshore Wind (TWh)	75	75	75	75	75	75	75
Offshore Wind (TWh)	75	75	75	75	75	75	75
Far Offshore Wind (TWh)	49.5	56	48.3	63.3	49.9	49.9	49.7
Hydro (TWh)	14	12.5	14.3	10.8	13.9	13.8	13.9
Biomass (TWh)	50	50	50	50	50	50	50
Wave (TWh)	50	50	50	50	50	50	50
Tidal Stream (TWh)	25	25	25	25	25	25	25
Solar PV (TWh)	50	50	50	50	50	50	50
Cost (£/MWh)	95.1	95	95	95	94.2	95.2	93.3
Risk (%)	**4.5**	4.5	4.5	4.4	**4.5**	**4.5**	**4.5**
CO_2 (Million Tonnes)	13.4	13.5	13.4	13.6	13.4	13.4	13.4
CO_2 Reduction from 1990 (%)	93.4	93.4	93.4	93.3	93.4	93.4	93.4

Table 8-26: Solar PV – Variability of optimal mix at point B

Point C on the efficient frontier has the largest variability of mix and cost and risk parameters out of the three chosen points to look more closely at. The risk values change -0.3% (0%, -0.7%) to maintain the baseline cost with the proportions of offshore wind, wave and gas with CCS increasing, and nuclear reducing.

Technology		Stationary Cost			Stationary Risk		
	Baseline	2080s 50%	2080s 10%	2080s 90%	2080s 50%	2080s 10%	2080s 90%
Gas (TWh)	0	0	0	0	0	0	0
Gas with CCS (TWh)	3.3	5.4	3.4	6.8	3.3	3.3	3.2
Coal	0	0	0	0	0	0	0
Coal with CCS (TWh)	0	0	0	0	0	0	0
Nuclear (TWh)	246	236	246.4	226.2	246	246	246
Onshore Wind (TWh)	75	75	75	75	75	75	75
Offshore Wind (TWh)	25.7	31.5	25.2	35.4	25.7	25.7	25.7
Far Offshore Wind (TWh)	0	0	0	0	0	0	0
Hydro (TWh)	25	25	25	25	25	25	25
Biomass (TWh)	50	50	50	50	50	50	50
Wave (TWh)	0	2.1	0	6.6	0	0	0
Tidal Stream (TWh)	25	25	25	25	25	25	25
Solar PV (TWh)	50	50	50	50	50	50	50
Cost (£/MWh)	**73.9**	**74**	**74**	**74**	73	74	72.1
Risk (%)	**10**	9.7	10	9.3	**10**	**10**	**10**
CO_2 (Million Tonnes)	0.1	0.2	0.1	0.3	0.1	0.1	0.1
CO_2 Reduction from 1990 (%)	99.9	99.9	99.9	99.9	99.9	99.9	99.9

Table 8-27: Solar PV – Variability of optimal mix at point C

8.4.3.4 Wave

Wave is limited to a maximum proportion of 10% of the energy mix for the 2050 constraints. Figure 8-25 shows the change in the baseline efficient frontier for changes in wave energy due to climate change. The sensitivity of the efficient frontier curve to reduced wave resource is larger in the lower risk, higher cost areas where wave energy is close to, or at its upper constraint level.

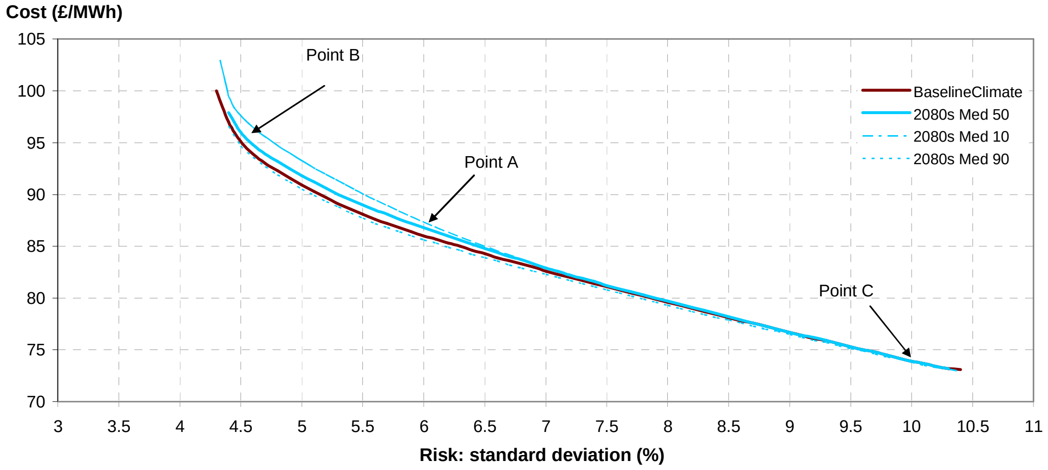


Figure 8-25: Impact of Wave Energy annual average climate variability on optimal portfolio mixes

Table 8-28 shows the cost and risk sensitivity respectively of the efficient frontier at the chosen optimal mix Points A, B and C.

Wave Energy Portfolio Variability	Cost Variability (£/MWh)		
	Point A	Point B	Point C
Baseline Climate	86.0	95.1	73.9
2080s Medium Emissions 50% (10%, 90%)	86.8 (87.3, 85.6)	96.0 (97.6, 94.7)	73.9 (73.9, 73.8)
	Risk Variability (% points)		
Baseline Climate	6.0	4.5	10.0
2080s Medium Emissions 50% (10%, 90%)	6.2 (6.3, 5.9)	4.6 (4.8, 4.5)	10.0 (10.0, 9.9)

Table 8-28: Portfolio cost and risk sensitivity –Wave Energy

Table 8-29 to Table 8-31 show the change in mix characteristics at Points A, B and C respectively on the efficient frontier.

Technology		Stationary Cost			Stationary Risk		
	Baseline	2080s 50%	2080s 10%	2080s 90%	2080s 50%	2080s 10%	2080s 90%
Gas (TWh)	0	0	0	0	0	0	0
Gas with CCS (TWh)	17.5	25.7	32.9	19.1	25.9	33.2	17.7
Coal	0	0	0	0	0	0	0
Coal with CCS (TWh)	11.5	21.2	30.1	13.7	21.9	31.3	11.4
Nuclear (TWh)	121.3	124.2	120.3	117.2	117.5	108.9	121.2
Onshore Wind (TWh)	75	75	75	75	75	75	75
Offshore Wind (TWh)	74.7	75	75	75	75	75	74.6
Far Offshore Wind (TWh)	0	0	16.7	0	0	26.6	0
Hydro (TWh)	25	25	25	25	25	25	25
Biomass (TWh)	50	50	50	50	50	50	50
Wave (TWh)	50	28.9	0	50	34.7	0	50
Tidal Stream (TWh)	25	25	25	25	25	25	25
Solar PV (TWh)	50	50	50	50	50	50	50
Cost (£/MWh)	**86**	**86**	**86**	**86**	86.8	87.3	85.6
Risk (%)	**6.0**	6.2	6.3	5.9	**6.0**	**6.0**	**6.0**
CO_2 (Million Tonnes)	1.8	3	4.1	2	3.1	4.2	1.8
CO_2 Reduction from 1990 (%)	99.1	98.5	98	99	98.5	97.9	99.1

Table 8-29: Wave Energy – Variability of optimal mix at point A

Technology		Stationary Cost			Stationary Risk		
	Baseline	2080s 50%	2080s 10%	2080s 90%	2080s 50%	2080s 10%	2080s 90%
Gas (TWh)	25	25	25	25	25	25	25
Gas with CCS (TWh)	4.1	3.7	4.1	4	4.1	4	3.9
Coal	0	0	0	0	0	0	0
Coal with CCS (TWh)	34.3	33.2	32.7	34.5	34.3	34.2	34.2
Nuclear (TWh)	48	55.2	65.3	46	48	48.2	48.2
Onshore Wind (TWh)	75	75	75	75	75	75	75
Offshore Wind (TWh)	75	75	75	75	75	75	75
Far Offshore Wind (TWh)	49.5	42.2	36.8	52.1	49.5	49.7	49.8
Hydro (TWh)	14	15.7	18.2	13.4	14	14	13.9
Biomass (TWh)	50	50	50	50	50	50	50
Wave (TWh)	50	50	42.9	50	50	50	50
Tidal Stream (TWh)	25	25	25	25	25	25	25
Solar PV (TWh)	50	50	50	50	50	50	50
Cost (£/MWh)	**95.1**	**95**	**95**	**95**	96	97.6	94.7
Risk (%)	**4.5**	4.6	4.8	4.5	**4.5**	**4.5**	**4.5**
CO_2 (Million Tonnes)	13.4	13.3	13.3	13.4	13.4	13.4	13.4
CO_2 Reduction from 1990 (%)	93.4	93.5	93.5	93.4	93.4	93.4	93.4

Table 8-30: Wave Energy – Variability of optimal mix at point B

Technology		Stationary Cost			Stationary Risk		
	Baseline	2080s 50%	2080s 10%	2080s 90%	2080s 50%	2080s 10%	2080s 90%
Gas (TWh)	0	0	0	0	0	0	0
Gas with CCS (TWh)	3.3	3.6	3.6	0	3.2	3.2	0
Coal	0	0	0	0	0	0	0
Coal with CCS (TWh)	0	0	0	0	0	0	0
Nuclear (TWh)	246	245.3	245.3	244.2	246	246	246.3
Onshore Wind (TWh)	75	75	75	75	75	75	75
Offshore Wind (TWh)	25.7	26.1	26.1	0	25.7	25.7	0
Far Offshore Wind (TWh)	0	0	0	0	0	0	0
Hydro (TWh)	25	25	25	25	25	25	25
Biomass (TWh)	50	50	50	50	50	50	50
Wave (TWh)	0	0	0	30.8	0	0	28.7
Tidal Stream (TWh)	25	25	25	25	25	25	25
Solar PV (TWh)	50	50	50	50	50	50	50
Cost (£/MWh)	**73.9**	**74**	**74**	**74**	73.9	73.9	73.8
Risk (%)	**10**	10	10	9.9	**10**	**10**	**10**
CO_2 (Million Tonnes)	0.1	0.1	0.1	0	0.1	0.1	0
CO_2 Reduction from 1990 (%)	99.9	99.9	99.9	100	99.9	99.9	100

Table 8-31: Wave Energy – Variability of optimal mix at point C

8.4.3.5 Hydro Energy

Figure 8-26 shows the sensitivity of the baseline efficient frontier to the climate variability of hydro for the 2080s. Hydro is constrained to an upper limit of 5% of the energy mix. There is an overall cost increase of around £0.5/MWh and change in risk of 0.1 – 0.2% points. There is slightly more cost and risk variability towards portfolio mixes with higher risk.

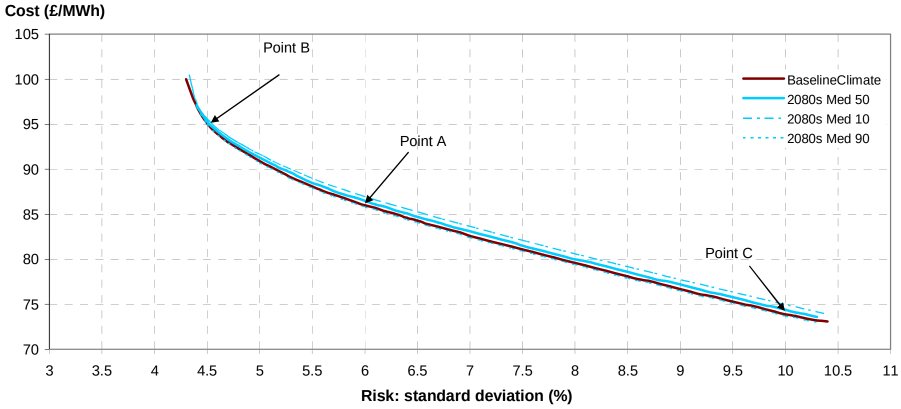


Figure 8-26: Impact of Hydro annual average climate variability on optimal portfolio mixes

Table 8-32 shows the cost and risk sensitivity of the efficient frontier to changing hydro.

Hydro Portfolio Variability	Cost Variability (£/MWh)		
	Point A	Point B	Point C
Baseline Climate	86.0	95.1	73.9
2080s Medium Emissions 50% (10%, 90%)	86.5 (87.0, 85.8)	95.3 (95.6, 95.0)	74.4 (75.0, 73.7)
	Risk Variability (% points)		
Baseline Climate	6.0	4.5	10.0
2080s Medium Emissions 50% (10%, 90%)	6.1 (6.3, 6.0)	4.5 (4.6, 4.5)	10.2 (10.4, 9.9)

Table 8-32: Portfolio cost sensitivity for fixed portfolio risk – Hydro Energy

Table 8-33 to Table 8-35 show the change in mix characteristics at Points A, B and C respectively on the efficient frontier. At Points A and B, hydro is generally below its upper constraint at the baseline and 2080s probability levels. At Point C, hydro is at its maximum for the baseline and 2080s climate.

		Stationary Cost			Stationary Risk		
	Baseline	2080s 50%	2080s 10%	2080s 90%	2080s 50%	2080s 10%	2080s 90%
Gas (TWh)	0	0	0	0	0	0	0
Gas with CCS (TWh)	17.5	17	16.5	18.2	17.4	19.4	17.5
Coal	0	0	0	0	0	0	0
Coal with CCS (TWh)	11.5	10.6	10.5	12.5	11.8	14.5	11.5
Nuclear (TWh)	121.3	126.4	134.1	119.3	121.8	123.8	121.3
Onshore Wind (TWh)	75	75	75	75	75	75	75
Offshore Wind (TWh)	74.7	72.5	73.4	75	75	75	74.7
Far Offshore Wind (TWh)	0	0	0	0	0	0	0
Hydro (TWh)	25	24.8	17.6	25	24	17.4	25
Biomass (TWh)	50	50	50	50	50	50	50
Wave (TWh)	50	48.8	47.7	50	50	50	50
Tidal Stream (TWh)	25	25	25	25	25	25	25
Solar PV (TWh)	50	50	50	50	50	50	50
Cost (£/MWh)	**86**	**86**	**86**	**86**	86.5	87	85.8
Risk (%)	**6.0**	6.1	6.3	6.0	**6.0**	**6.0**	**6.0**
CO_2 (Million Tonnes)	1.8	1.7	1.6	1.9	1.8	2.1	1.8
CO_2 Reduction from 1990 (%)	99.1	99.2	99.2	99.1	99.1	99	99.1

Table 8-33: Hydro – Variability of optimal mix at point A

		Stationary Cost			Stationary Risk		
	Baseline	2080s 50%	2080s 10%	2080s 90%	2080s 50%	2080s 10%	2080s 90%
Gas (TWh)	25	25	25	25	25	25	25
Gas with CCS (TWh)	4.1	3.9	3.9	4	3.8	7.9	3.8
Coal	0	0	0	0	0	0	0
Coal with CCS (TWh)	34.3	34	34	34.2	34.3	32.4	33.9
Nuclear (TWh)	48	51.3	54.4	47.6	48.9	48.2	47.9
Onshore Wind (TWh)	75	75	75	75	75	75	75
Offshore Wind (TWh)	75	75	75	75	75	75	75
Far Offshore Wind (TWh)	49.5	47.3	45.6	49.9	50.1	49.7	50
Hydro (TWh)	14	13.3	12	14.3	13	11.8	14.4
Biomass (TWh)	50	50	50	50	50	50	50
Wave (TWh)	50	50	50	50	50	49.9	50
Tidal Stream (TWh)	25	25	25	25	25	25	25
Solar PV (TWh)	50	50	50	50	50	50	50
Cost (£/MWh)	**95.1**	**95**	**95**	**95**	95.3	95.6	95
Risk (%)	**4.5**	4.5	4.6	4.5	**4.5**	**4.5**	**4.5**
CO_2 (Million Tonnes)	13.4	13.4	13.4	13.4	13.4	13.4	13.4
CO_2 Reduction from 1990 (%)	93.4	93.4	93.4	93.4	93.4	93.4	93.4

Table 8-34: Hydro – Variability of optimal mix at point B

		Stationary Cost			Stationary Risk		
	Baseline	2080s 50%	2080s 10%	2080s 90%	2080s 50%	2080s 10%	2080s 90%
Gas (TWh)	0	0	0	0	0	0	0
Gas with CCS (TWh)	3.3	3.5	24.6	4	3.7	3.7	3.3
Coal	0	0	0	0	0	0	0
Coal with CCS (TWh)	0	0	0	0	0	0	0
Nuclear (TWh)	246	250	250	243.2	245.9	245.9	246
Onshore Wind (TWh)	75	75	75	75	75	75	75
Offshore Wind (TWh)	25.7	21.5	0	27.8	25.4	25.4	25.6
Far Offshore Wind (TWh)	0	0	0	0	0	0	0
Hydro (TWh)	25	25	25	25	25	25	25
Biomass (TWh)	50	50	50	50	50	50	50
Wave (TWh)	0	0	0	0	0	0	0
Tidal Stream (TWh)	25	25	25	25	25	25	25
Solar PV (TWh)	50	50	50	50	50	50	50
Cost (£/MWh)	**73.9**	**74**	**74**	**74**	74.4	75	73.7
Risk (%)	**10**	10.2	10.4	9.9	**10**	**10**	**10**
CO_2 (Million Tonnes)	0.1	0.1	1	0.2	0.2	0.1	0.1
CO_2 Reduction from 1990 (%)	99.9	99.9	99.5	99.9	99.9	99.9	99.9

Table 8-35: Hydro – Variability of optimal mix at point C

8.4.4 Comparison of individual and collective technology impact on optimal energy mixes

This comparison gives an example of the cost and risk variability of an optimal mix to annual average climate variability of individual and collective technologies. The values are based on all analysis performed in sections 8.4.2 and 8.4.3. The technology parameters are for the 2050s and the climate is the 2080s, these have been chosen to explore the maximum annual average climate variability of the full range of time periods. It can be seen (Table 8-36) that the cost of an optimal mix could vary by as much as 9.3 £/MWh or by as much as 2.0 percentage points of portfolio risk. This would actually be more if it were not for solar PV which is the only technology that experiences an increased resource due to climate change. Offshore wind is the largest contributor towards the variability, though in this example it has an upper constraint of 30% of the energy mix which will allow it to cause more variability than others that are more constrained.

Point B shows the largest cost and risk variability and Point C shows the lowest variability. There is a larger proportion of renewables at Point B due to it being a low risk mix, which many renewable technologies are. Point C is at the other extreme, being a low cost high risk mix with fewer renewable technologies in the mix.

Technology	Upper Constraint	Portfolio Cost Variability MWh			Portfolio Risk Variability Percentage Points		
		Point A	Point B	Point C	Point A	Point B	Point C
Onshore Wind	15	1	1.1	1.1	0.3	0.1	0.3
Offshore Wind	30	2.3	4.8	0.2	0.5	0.4	0.2
Solar	10	1.8	1.1	1.9	0.4	0.1	0.7
Wave	10	1.7	2.9	0.1	0.4	0.3	0.1
Hydro	5	1.2	0.6	1.3	0.4	0.1	0.5
All	**-**	**7.5**	**9.3**	**3.4**	**1.6**	**2**	**1.2**

Table 8-36: Cost and risk variability of optimal mixes

8.5 MVPT Summary

The sensitivity of future optimal portfolio mixes to climate change has been investigated and it has been concluded that climate change could significantly change the cost and risk characteristics of optimal technology mixes and could also render the mix sub-optimal for a future climate.

MVPT has been successfully employed to analyse the sensitivity of optimal electricity generation mixes to climate change. This has been performed for three technology cost projection time periods (2010, 2020 and 2050) and three climate periods (baseline, 2050s and 2050s). The climate change impact has been evaluated by comparing MVPT output for the baseline climate with probabilistic output for the 2050s and 2080s time periods. The probabilistic climate data allows the climate uncertainty to be captured within the results.

Different required MVPT input parameters have been discussed and appropriate sets of values determined. Cost risk values were plotted for all individual technologies and these clearly showed the levelised cost uncertainty of solar PV, on- and offshore wind, wave and hydro, due to climate change. Also discussed and determined were different sets of technology mix constraint values for the MVPT analysis which were chosen specifically to suit the different time periods of interest.

9 Discussion and Conclusion

9.1 Thesis Summary

The thesis comprises of 9 chapters. Chapter 1 introduced the objectives, scope and contribution to knowledge. The hypothesis that the thesis aims to answer was stated as:

> *Physical climate change will affect renewable energy resources in such a way that its impact may be likely to leave future optimal UK electricity generation portfolios sub-optimal.*

Chapter 2 was intended to equip the reader with sufficient, but not exhaustive knowledge and essential material to provide a background to the main topics of interest covered in the thesis. The literature review covered climate change, renewable energy resource and technologies, electricity generation economics and risk, security of supply, diversity, CO_2 emission reduction, mean variance portfolio theory (MVPT) and its application in energy systems. Based on the outcome of the literature review a gap analysis identified that exploration of the impact of climate change on portfolios of electricity generation was a novel endeavour. An outline of the necessary framework of work to be undertaken in the rest of the thesis was given. It suggested that initial work focus on development of renewable resource models for a range of technologies, prior to bringing them together to estimate changes to cost and risk.

Chapter 3 explored the spatial variation of solar energy resource across the UK and developed a monthly average model of solar radiation. It then investigated the impact climate change could have on the resource and output (TWh) from solar photovoltaic (PV) cells. Accurate estimations of mean monthly solar radiation resource were generated and validated from mean monthly sunshine duration measurement data. Baseline models of present climate UK solar radiation, solar PV output on the horizontal plane and at an optimal south facing inclination was developed and validated. UKCP09 probabilistic data was then used to show relative monthly climate change impact over the UK for the 2050s and 2080s. The results showed that by the 2050s, with a medium emissions scenario, the UK will see an overall solar radiation annual increase of 2.6% (within a range of -1.1% to 6.5%). Summer months will see increases of up to 7.9% (within a range of -0.2% to 18.1%) in the south west, these reduce further north with decreases of up to -2.9% (within a range of -10.8% to 1.8%) in the north of Scotland. Winter months show a reduction throughout the UK with extremes of -7.6% (within a range of -25.2% to 10.1%) in mid-west Scotland. This showed that most parts of the southern UK will get sunnier and benefit from increased solar energy resource in summer, while the relatively poor resources in the north will decrease slightly. All regions in winter will have increased cloud cover and slightly reduced solar energy resource.

Chapter 4 explored UK monthly average onshore wind resources for the current, 2050s and 2080s climates. Monthly gridded sets of observed onshore wind speed data were used to generate a baseline wind speed and wind energy resource model. The actual positions and sizes of all known operating and potential future wind farm locations were projected onto the baseline wind energy output model before output for each of the locations were collected and accumulated to create a UK onshore wind energy model that closely reflected the actual present and future distribution of UK onshore wind farms. In the absence of UKCP09 probabilistic projections for wind, output from the HadRM3 ensemble runs were used to generate probabilistic wind climate change projections for the 2050s and 2080s periods. The changes were applied to the baseline wind speed model and future wind energy output was generated for the 2050s and 2080s and changes in the accumulated UK onshore wind farm resource were explored. The 2050s appear to indicate slight negative changes in wind speed ranging in the extreme to approximately -5.0% (-10.5% to 0.4%) in the 2050s and -6.9% (-12.8% to -1.0%) in the 2080s. The results showed that the overall annual wind energy output from all onshore wind turbine sites in operation and planned is estimated to be in the region of 38 TWh with the current climate. It is estimated that climate change could change this by -0.6% (-5.6% to 4.1%) for the 2050s and -1.4 (-6.7% to 3.5%) for the 2080s. The future onshore wind energy resource is more seasonally variable, with (slight) increases in winter months, when resource is at its best; and (slight) decreases in some summer months.

Chapter 5 explored the UK offshore wind resource model for the current, 2050s and 2080s climates using averaged monthly wind speed data from the HadRM3 data set. A UK offshore wind farm baseline resource model was created to closely reflect the actual present and future distribution of offshore wind farms. Monthly averaged output (TWh) for each location were collected and accumulated to complete the UK offshore wind farm resource model. Projected wind energy models for the 2050s and 2080s were created in the same way as described for the baseline models. The projected climate variability of wind speed wind energy and the UK offshore wind farm resource model was explored by comparing the baseline data with the projected future data. The results showed negative annual average climate changes in wind speed of typically -1.8% (-9.3% to 1.6%) for the 2050s medium emissions scenario and -3.0% (-8.1% to 2.0%) for the 2080s. The overall annual wind energy output from all offshore operational and potential wind turbine sites is estimated to change by -2.1% (-7.6% to 2.8%) for the 2050s and -1.4 (-6.7% to 3.5%) for the 2080s. The intra-annual climate changes show the future offshore wind energy resource to be more seasonally variable. In summer months when resource is lower there is a significant reduction. July has an estimated change of -3.3% (-22.4% to 14.7%) for the 2050s and -8.5% (-28.3% to 11.0%). In comparison, January has a change of 0.0% (-1.2% to 0.4%) for the 2050s and -0.3% (-1.8% to 0.3%) for the 2080s.

Chapter 6 investigated and discussed other electricity generation technologies that may be affected by climate change. The potential sensitivity of wave energy resource to climate variability was examined by converting baseline and future wind speed data at specific locations to wave resource using a first generation wave model, and to wave energy production estimates using the power curve of a wave energy converter. The results showed that by the 2050s for a medium emissions scenario, the projected annual average output of the WEC used in this study, will change by approximately -1.4% (-7.0 to 3.4) in the far north to -3.8% (-10.4 to 2.5) in the far south. In the 2080s changes are stated as -2.7% (-9.2 to 3.0) in the far north to -5.2% (-13.3 to 2.1). The intra-annual climate variability show the resource will be more seasonably variable with winter months (which typically have larger resource than summer months) having a slight decrease in wave resource (typically -0.25% (-0.4 to 0.1) for the 2050s), and summer months experiencing a substantial reduction which appears to increase towards more southerly locations. Changes in hydropower resource were based on complex hydrological analysis by Duncan (2012). The capacity factor figures are based on modelled hydropower plants in 5 catchment areas in Scotland. The resource for the baseline and future time periods have been estimated by modelling river flow in the catchment areas using observations for the baseline period (1961-1990) and output from the UKCIP09 (2009) weather generator for the 2050s medium emissions scenario respectively. The results indicate an overall annual change in energy output of approximately -4.0% (6.3% to -14.3%) for the 2050s medium emissions climate. There is an increase in winter months of approximately 2.4% (-2.2% to 7.2%) in December. However, in summer there are significant reductions in production, approximately -29.5% (-11.1% to 47.9%) in August. Other renewable and non-renewable generation technologies were not examined in this work.

Chapter 7 developed sets of levelised cost estimations for different generation technologies including renewable and non-renewable technologies. Its aim was to provide a coherent and comparable set of figures for portfolio analysis. A study of the sensitivity of levelised costs of technologies to varying discount rates was also performed to highlight how technologies were affected in different ways. This showed levelised costs to be very sensitive to discount rate for capital intensive technologies, such as renewables, and much less sensitive for technologies that have higher levels for fuel and CO_2 costs throughout the lifetime of the project. Sample cost projections were delivered for 2010, 2020 and 2050 and these were combined with annual average climate variability estimates to create a range of changes in cost of generation under climate change. These showed substantial variability in response.

Finally, Chapter 8 brought together the data and findings from previous chapters and used them as input to MVPT analysis to test the hypothesis. MVPT was successfully used as an analysis tool to explore the sensitivity of optimal electricity generation mixes to climate change. This was performed for three technology cost projection time periods (2010, 2020 and 2050) and three climate periods (baseline, 2050s and 2080s). The climate change impact was evaluated by comparing MVPT output for the baseline climate with probabilistic output for the 2050s and 2080s time periods. The probabilistic climate data allowed the climate uncertainty to be captured within the results. The results showed that climate change could significantly change the cost and risk characteristics of optimal portfolio mixes. As an example, for a portfolio mix comprising largely of wind, wave, solar and nuclear, the 2080s climate changed an optimal mix baseline climate cost of £95.1/MWh to £96.5/MWh, or the baseline risk of 4.5% to 4.7% (4.3%, 5.3%), when expressed in change of portfolio risk.

9.2 Thesis Results

In Chapter 8, using data and results from the previous chapters, it was demonstrated that the effects of climate change could affect renewable energy in such a way that its impact may be likely to leave future optimal UK electricity generation portfolios sub-optimal. The thesis hypothesis was tested using MVPT analysis with input technology cost-risk parameters to reflect 2010, 2020 and 2050. The MVPT analysis was run for different climate periods: current climate and probabilistic climate projections for the 2050s and 2080s using a medium emissions scenario.

The main test case was performed using 2050 technology input parameters and constraint values. MVPT analyses were performed using technology resource for the baseline climate and the 2080s climate. The reason for choosing the 2050s technology period is that the MVPT constraints are more relaxed and the MVPT analysis is allowed to choose optimal mixes with larger proportions of renewables. The reason for choosing the 2080s is that this period has larger annual average climate variability than the 2050s. Three optimal mixes (A, B and C) were identified on the baseline optimal portfolio curve. ‘A’ is in a mid-point optimal mix on the curve, ‘B’ is a low-cost optimal mix, and ‘C’ is a low-risk optimal mix. To measure change in portfolio two analyses are performed: the change in portfolio risk at the same cost as the current climate; and the change in portfolio cost at the same risk as the current climate.

Example of the results: When MVPT analysis was run for the baseline climate, the optimal mix at ‘Point A’ had an expected cost and risk of £86.0/MWh and 6.0% respectively. However, with 2080s climate resource, the expected cost and risk values change. To maintain the expected portfolio cost at £86.0/MWh, the resulting expected risk will change by 0.2 (1.0, -0.3) percentage points, or by 3.3% (16.7% to -11.7%) in relative terms. The technology mix will need to change by values shown in Table 9-1. The main changes are a substantial reduction of wave energy which is replaced by a mix of coal and gas with CCS and some nuclear. There is a resulting effect of marginally increased CO_2 emissions.

Technology	Actual	Change to maintain cost			Change to maintain risk		
	Baseline Mix A	2080 50%	2080 10%	2080 90%	2080 50%	2080 10%	2080 90%
Gas (TWh)	0	0	0	0	0	0	0
Gas with CCS (TWh)	17.5	+8.2	+19	+8.6	8.2	19.7	-0.2
Coal	0	0	0	0	0	0	0
Coal with CCS (TWh)	11.5	+9.7	+21.2	+12.6	10.5	24.5	-0.1
Nuclear (TWh)	121.3	+2.7	+21.5	-30.8	-3.7	-12.5	0
Onshore Wind (TWh)	75	0	0	0	0	0	0
Offshore Wind (TWh)	74.7	+0.3	-11.7	+0.3	0.3	0.3	0.3
Far Offshore Wind (TWh)	0	0	0	+10.1	0	0	0
Hydro (TWh)	25	0	0	-0.8	0	0	0
Biomass (TWh)	50	0	0	0	0	0	0
Wave (TWh)	50	-21	-50	0	-15.3	-32	0
Tidal Stream (TWh)	25	0	0	0	0	0	0
Solar PV (TWh)	50	0	0	0	0	0	0
Cost (£/MWh)	86	0	0	0	0.7	4.7	-3
Risk (%)	6	+0.2	+1	-0.7	0	0	0
CO_2 (Million Tonnes)	1.8	+1.2	+2.7	+1.5	1.3	3	-0.1
CO_2 Reduction from 1990 (%)	99.1	-0.6	-1.3	-0.7	-0.6	-1.5	0

Table 9-1: Change required to maintain baseline expected cost and expected risk at values for optimal mix A for the 2080s climate

To maintain the expected portfolio risk at 6.0% the resulting expected cost will change by £0.7/MWh (£4.7/MWh to -£3.0/MWh) or by 0.8% (5.5% to -3.5%) in relative terms.

The mix will need to change by values shown in Table 9-1. The main changes are similar to the previous results for maintaining cost but not quite as much reduction of wave energy and a small reduction in nuclear too.

Each technology was also individually tested. The technology on test was changed from its baseline to 2080s climate resource. All others were kept at their baseline resource. The effect of the individual technology on optimal portfolios was tested at each of the three optimal mix points (A, B and C) as described earlier. The figures shown in Table 9-2 describe the results. Solar PV is the only technology that reduces the portfolio cost and risk from baseline climate resource levels to 2080s medium emissions resource levels. This is due to increased solar resource. The other technologies increase the optimal mix costs and risks. The upper constraint on the technology needs to be taken into account when comparing between technologies.

Technology	Constraint	Point A	Point B	Point C
		Baseline Cost and Risk: £86.0 /MWh 6.0%	Baseline Cost and Risk: £95.0 /MWh 4.5%	Baseline Cost and Risk: £73.9 /MWh 10.0%
		Cost Variability (£/MWh)		
Solar PV	10%	85.1 (86.1, 84.2)	94.2 (95.2, 93.3)	73.0 (74.0, 72.1)
Onshore Wind	15%	86.2 (86.7, 85.7)	95.2 (95.8, 94.7)	74.1 (74.7, 73.6)
Offshore Wind	30%	86.7 (87.9, 85.6)	96.4 (99.0, 94.2)	74.0 (74.0, 73.8)
Wave	10%	86.8 (87.3, 85.6)	96.0 (97.6, 94.7)	73.9 (73.9, 73.8)
Hydro	5%	86.5 (87.0, 85.8)	95.3 (95.6, 95.0)	74.4 (75.0, 73.7)
		Risk Variability (% points)		
Solar PV	10%	5.8 (6.0, 5.6)	4.5 (4.5, 4.4)	9.7 (10.0, 9.3)
Onshore Wind	15%	6.1 (6.2, 5.9)	4.6 (4.6, 4.5)	10.1 (10.3, 10.0)
Offshore Wind	30%	6.2 (6.4, 5.9)	4.6 (4.8, 4.4)	10.0 (10.0, 9.9)
Wave	10%	6.2 (6.3, 5.9)	4.6 (4.8, 4.5)	10.0 (10.0, 9.9)
Hydro	5%	6.1 (6.3, 6.0)	4.5 (4.6, 4.5)	10.2 (10.4, 9.9)

Table 9-2: Cost and risk portfolio sensitivity of individual technologies for the 2080s climate at optimal mix points A, B and C

9.3 Thesis Conclusions

The aim of the work in this thesis was to test the hypothesis that:

> *Physical climate change will affect renewable energy resources in such a way that its impact may be likely to leave future UK electricity generation portfolios sub-optimal.*

The results from the MVPT analysis, pulling in all the findings from the previous chapters, suggest the hypothesis to be true, although there is substantial uncertainty.

All stages of the study (resource assessments for baseline and future climates, conversion to technology, levelised cost calculations, MVPT analysis) have been performed in an internally consistent and comparable way.

The work undertaken to prove the hypothesis delivered several novel outcomes.

- First analysis of probabilistic climate change on solar resource the UK;

- New model to convert the HadRM3 ensemble into a probabilistic structure ahead of the recent UKCP09 probabilistic wind speeds;
- First analysis of probabilistic climate change on offshore wind;
- First analysis to analyse future wave energy at multiple sites and within a probabilistic framework;
- First multi technology study performed in an integrated way;
- First to explicitly link portfolio theory and climate change;
- First to include resource levels and uncertainty to MVPT;

The thesis contribution to knowledge includes all the above novel findings as well as successfully completing the main objective which was investigate the impact of climate change on optimal electricity generation mixes. There are also several resource / energy resource maps of the UK for current and future probabilistic climates. The thesis outcome provides a toolkit containing tools that can be used to bring economic understanding towards climate change. The work covered in this thesis underpins a £1.4m EPSRC project titled 'Adaptation and Resilience in Energy Systems' (ARIES).

While the work does not explicitly consider adaptation, understanding the vulnerabilities of electricity generation technologies to climate change can help in adaptation of the energy system towards making it more resilient to climate change effects. There are many challenges in meeting energy reduction targets and changing to a low carbon system. The approach to the 2050 and the 80% GHG reduction target will see electricity generation system change dramatically. Mature and emerging renewable technologies will play a much larger role. This study highlights vulnerabilities in renewable technologies and optimal portfolios to climate change.

Renewables can be matched to the resource of the specific locations. The matching should also incorporate expected climate variability. For example, wind farms to be situated in locations that are likely to experience increased wind speeds due to climate change could be deployed with a higher specification wind turbine design.

Electricity generation mixes could take climate change into account. For example, solar PV resource and the climate change impact on the resource is negatively correlated with the resource of other technologies such as wind, wave and hydro technologies, and has the potential to counterbalance the negative effects of those renewable technologies. This has been clearly shown in section 8.4.2. One of Awerbuch's important implications when discussing 'essential portfolio-theory ideas' and the fact that the environment is dynamic and has uncertainties, is that the relative value of electricity generation technologies should be determined by evaluating alternative resource portfolios and not by evaluating the individual resources in isolation (Awerbuch 2006). This is definitely the case when evaluating the benefits of solar PV being a very diverse technology when compared to the intra annual characteristics of other renewable technologies.

9.4 Thesis Limitations

While the work has delivered a great deal, there are undoubtedly limitations. The thesis is very broad in the sense it covers many areas and each of these is individually suitable for PhD study. Due to the broadness and finite time of the PhD is was necessary to limit the complexity of the many models but to ensure they were as robust and effective as possible and that they captured the essence of each problem. It was considered whether a very deep analysis would deliver more insight towards the testing of the hypothesis. However, it was decided that, except for potentially reducing some uncertainties, it probably wasn't the case.

The impact of climate change on optimal portfolios was investigated for only the 'medium emissions' scenario. This was due to the HadRM3 data set, required for wind speed, having only been run for the one scenario, which restricted the opportunity for cross comparisons. The MVPT analysis chapter focused on comparing the 2080s and baseline climate using 2050 projection costs and constraints to prove the hypothesis. Ideally, the analysis would have been performed for several different combinations of costs and climate.

Ideally, CO_2 emissions from a chosen optimal mix would then trigger the future climate scenario to test the impact of the chosen optimal mix. For example, a mix with 90% CO_2 reduction may be aligned with the GHG emissions that represent the low emissions scenario, and a mix with only 50% CO_2 reduction may be aligned with the high emission scenario. However, this would only be possible if the rest of the world were also aligned with the emission reductions, which may not be feasible.

The MVPT analysis method fails to capture the intra-annual variability of renewable technologies and the added financial risk that this may add. Akin to Awerbuch's fuel price volatility analysis in Chapter 2. All investigated technologies showed more extreme intra-annual variability, but MVPT only captures the levelised cost value, which is calculated using the annual energy output, and the intra-annual variability of energy output does not feature in the calculation of risk. However, it is also worth pointing out that the intra-annual variability of fuel is not captured in the risk calculation of thermal plant risk.

The MVPT analysis performed in this study is based on historical cost co-variance data, which is generally the case with traditional MVPT analysis. However, there is uncertainty associated with how valid it is to assume future cost characteristics will remain the same as historical observations. There is also the argument that historical risk characteristics will not capture future events that have not previously happened.

Levelised costs were generated for 2010 and 2020 technology input parameters. Ideally, costs for 2050 would also have been generated, but weighing up the inherent uncertainty of costs, and the confidence in projecting comparable costs 40 years into the future, it was decided to make an assumption that all technologies would advance in such a way that costs would stay relatively comparable from 2020 values. The 2050 values were used to represent advancement in deployment. A sensitivity study on discount rate was performed to highlight the way in which different technologies are affected by the discount rate; however, the effect of different discount rates on MVPT output has not been shown, neither has the sensitivity to varying fuel and CO_2 costs.

There are several renewable and non-renewable technologies not included in this thesis, that are potentially susceptible to climate change and the thesis would be more complete if it contained them. However, it is thought that the thesis includes the technologies that are most at risk from climate change.

The conversion of resource to product has been performed using only one technology model in each case. Ideally, the analysis would feature several different devices to capture a more complete spectrum of devices. This is especially true for emerging technologies like wave, where there are many differing types of technology.

There are many uncertainties associated with the different steps in the thesis, most of which have been highlighted throughout. It is very difficult to compare the magnitude of climate change uncertainty with the other uncertainties and would need an in depth review to accomplish this. The uncertainties all cascade together and inherently grow larger relative to the time period under investigation. Climate change uncertainty is just one in a basket of uncertainties all of which need consideration.

9.5 Recommendations for Further Work

Below are recommendations of further work that could be undertaken to extend the work performed in this thesis. The list is not exhaustive, neither is it sorted by importance or level of contribution. Each recommendation would need to be properly assessed and weighed up against the additional resource and timescales it would require, prior to being actually performed.

Include additional technologies susceptible to climate change in the overall analysis:

- Thermal plant, tidal stream, biomass and biofuels, others.

Improve MVPT analysis:

- Find a method to incorporate the intra-annual and inter-annual variability of renewable resource into the MVPT risk analysis. Extend the method to incorporate intra-annual fuel risk for the non-renewable technologies.
- Investigate and update the historical cost information that is the basis of the technology risk and cost correlations. Investigate other potential methods of estimating risk and diversity that can be applied to MVPT analysis of future time periods.
- Look into incorporating a Monte Carlo simulation approach to add probability distributions of future fuel and CO_2 cost and risk into the analysis.
- Perform MVPT analysis on a larger set of input scenarios (climate time period, estimated costs, emissions scenarios).
- Review the technology constraints for future time periods. Perform MVPT analysis on a larger set of constraint values for each future time period.

Improve levelised cost values:

- Include sets of levelised cost values that cover sensitivities of fuel price and CO_2 price variability, as well as uncertainties.
- Generate levelised cost estimates for the 2050s. As discussed, this may take quite a lot of effort to generate values that are consistent and comparable for a time period so far into the future.

Improve Solar Resource Model:

- Incorporate the hourly characteristics of baseline resource and future resource. The current model assumes uniform cloud cover over the day period.
- Further investigate optimal angle using more detailed hourly time series data: This potentially could follow the method of Li *et al.* (2007) and possibly Lorenzo (2005). The method used by Li *et al.* used data over a year period with ten minute time samples.
- Add more complexity into the conversion to technology, for example incorporating the temperature – efficiency relationship to the solar PV profile, and add more technical choices of technology.
- Improve the modelling of technology deployment. Possibly distribute deployment relative to rooftop space as well as locations with the best resource.
- Incorporate topology and shading into future resource assessment.

Improve Wind Resource Model:

- Possibly implement Weibull distribution in the wind analysis. This has the potential of more closely following actual wind characteristics. However, it is difficult to apply over large areas and requires local wind characteristic input. On reflection, unless the wind characteristics were analysed over many locations over the UK, the Rayleigh is potentially the better option due to the large are covered by the UK.
- Implement roughness characteristics into the conversion of wind speed to different heights. This would improve the accuracy of conversion of wind speed to different heights. However, like the Weibull distribution, it is difficult to implement over large areas and requires local surface characteristic input.
- Incorporate the Edinburgh Wind Model (Hawkins 2012) into the on- and offshore wind resource analysis.
- Introduce other wind turbine characteristics to the model. Currently only one wind turbine profile is used in the analysis.

Improve Wave Resource Model:

- Improve the complexity of the wave resource study by using a wave model driven by wind output from a RCM, which is ideally driven by the HadRM3 11-member ensemble.
- Introduce other wave device characteristics to the model.

Other general resource assessment improvements:

- Incorporate current and future time series of data in the analysis. This would enable the study to consider changes that are not captured by the long-term average monthly data; for example, diurnal weather pattern changes and frequency of extreme weather. The UKCP09 weather generator output would potentially be a good tool to perform this, or the mesoscale weather model that will be developed in the ARIES project.

Investigate whether possible to integrate / soft couple the model to the MARKAL model used in the UKERC 2050 project.

9.6 Thesis Final Conclusion

The thesis describes an attempt to assess the impact of climate change on optimal low carbon electricity generation technologies using MVPT analysis. Many areas are explored in differing detail in order to quantify the sensitivity of optimal electricity generation mixes to climate change. There are several gaps in the overall analysis but it is thought that this thesis is a reasonable and conclusive study which forms a credible basis for further exploration of the impact of climate change on electricity generation technologies and optimal portfolios.

References

AEA Technology (2011a). Pathways to 2050 – Key Results. Report for the *Department of Energy and Climate Change*.

AEA Technology (2011b). Pathways to 2050 – Detailed Analyses. Report for the *Department of Energy and Climate Change*.

Allan, G. Gilmartin, M. McGregor, P. Swales, K. (2010). Levelised costs of wave and tidal energy: Current cost comparison and the impact of ‘banded’ Renewable Obligation Certificates. Energy Policy, Vol. 39, No. 1, p. 23-39.

Allan, G. Eromenko , I. McGregor, P. Swales, K. (2011). The regional electricity generation mix in Scotland: a portfolio selection approach incorporating marine renewables. Energy Policy, Vol. 39, No. 1, p. 6-22.

Anandarajah G, Strachan N, Ekins P, Kannan R, Hughes N (2009) Pathways to a Low Carbon Economy: Energy Systems Modelling, *UK Energy Research Centre* (UKERC) Energy 2050 Research Report 1.

Awerbuch, S. (2000) ‘Investing in Photovoltaics: Risk, Accounting and the Value of New Technology,’ *Energy Policy*, **28** (14).

Awerbuch, S., Berger, M. (2003). Energy Security and Diversity in the EU: A Mean-Variance Portfolio Approach, Report Number EET/2003/03, *International Energy Agency*, Paris.

Awerbuch, S. (2003b). Determining the real cost: why renewable power is more cost-competitive than previously believed. *Renewable Energy World* 6(2), March–April 2003.

Awerbuch, S. (2005a) ‘The Role of Wind in Enhancing UK Energy Diversity and Security: A Mean-Variance Optimization of the UK Generating Mix’. Retrieved November 2011 from: URL: http://www.awerbuch.com

Awerbuch, S. (2005b). ‘The Role of Wind Generation in Enhancing Scotland’s Energy Diversity and Security: A Mean-Variance Portfolio Optimization of Scotland’s Generating Mix’. Retrieved November 2011 from: http://www.awerbuch.com

Awerbuch, S., Jansen, J., Beurskens, L. Drennen, T. (2005b). ‘The Cost of Geothermal Energy in the Western US Region: A Portfolio-Based Approach. A Mean-Variance Portfolio Optimization of the Region’s Generating Mix to 2013’. *Sandia National Laboratories*. SAND2005-5173.

Awerbuch, S. (2006) Portfolio-based electricity generation planning: policy implications for renewables and energy security. *Mitigation Adapting Strategies Global Change*, 11 3, pp. 693–710.

Awerbuch, S., Sauter, R., (2006). Exploiting the oil–GDP effect to support renewables deployment. *Energy Policy*, 34(17), 2805-2819. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0301421505001230.

Awerbuch, S., Yang, S. (2007). Efficient Electricity Generating Portfolios for Europe: Maximising Energy Security and Climate Change Mitigation. *European Investment Bank* (EIB) Papers. Volume 12 No2 2007.

Barrow Offshore Wind Limited (BOW). (2008). The Project. Retrieved March 2011 from http://www.bowind.co.uk/project.shtml

Barthelmie RJ, Frandsen ST, Nielsen NM, Pryor SC, Rethore PE, Jørgensen HE. (2007). Modelling and measurements of power losses and turbulence intensity in wind turbine wakes at Middelgrunden offshore wind farm. *Wind Energy* 2007; 10: 217–228.

Barthelmie RJ, Hansen K, Frandsen ST, Rathmann O, Schepers JG, Schlez W, *et al*. (2009). Modelling and measuring flow and wind turbine wakes in large wind farms offshore. *Wind Energy* 2009;12(5):431e44.

Barthelmie, R. Jensen, L. (2010). Evaluation of wind farm efficiency and wind turbine wakes at the nysted offshore wind farm. *Wind Energy*, 13.

Bazilian, M and Roques, F. (2008) *Analytical Methods for Energy Diversity and Security*, Elsevier, Oxford.

BERR, (2008a). Atlas of UK Marine Renewable Energy Resources. © Crown Copyright. All rights reserved 2008. Retrieved March 2011 from http://www.renewables-atlas.info/wind_map.aspx

BERR, (2008b). Atlas of UK Marine Renewable Energy Resources: Technical Report. © Crown Copyright. All rights reserved. Retrieved March 2011 from http://www.renewables-atlas.info/downloads/documents/R1432_Final_15May08.pdf

BERR (2004-2009). Offshore Wind Capital Grants Scheme Annual Reports. Retrieved March 2011 from http://webarchive.nationalarchives.gov.uk/+/http://www.berr.gov.uk/energy/environment/etf/offshore-wind/page45496.html

BERR wind speed database. © Crown Copyright. All rights reserved 2008. Retrieved May 2011 from http://webarchive.nationalarchives.gov.uk/+/http://www.dti.gov.uk/energy/sources/renewables/renewables-explained/wind-energy/page27708.html

Breslow, P.B., Sailor, D.J.(2002). Vulnerability of wind power resources to climate change in the continental United States. Renewable Energy. 27:585-98.

Burnett, D., Harrison, G. (2010). Climate change and the UK solar energy resource, *Future Climate and Renewable Energy: Impacts, Risks and Adaptation*, 31 May-2 June 2010, Oslo, Norway (See Appendix F).

Cassman, K. G. (2007). Climate change, biofuels, and global food security. *Environmental Research Letters 2*:doi:10.1088/1748-9326/1082/1081/011002.

Commission of the European Communities. (2007). An Energy Policy For Europe. Communication from the Commission to the European Council and the European Parliament. Retrieved January 2012 from http://ec.europa.eu/energy/energy_policy/doc/01_energy_policy_for_europe_en.pdf

Cradden, L. (2009). The Impact of Climate Change on Wind Energy Generation in the UK. PhD Thesis. The University of Edinburgh.

Crook, J.A. *et al.*, (2011). Climate change impacts on future photovoltaic and concentrated solar power energy output. *Energy & Environmental Science*, 4(9), 3101. Available at: http://xlink.rsc.org/?DOI=c1ee01495a.

Crown Estate (2010a). World's first wave and tidal energy leasing round to power up to three quarters of a million homes. Accessed October 2011: http://www.thecrownestate.co.uk/newscontent/92-pentland-firth-developers.htm

Crown Estate (2011). Current wave and tidal activity. Accessed October 2011: http://www.thecrownestate.co.uk/current-wave-tidal-uk.pdf

DECC (2008). Climate Change Act 2008. Available from http://www.decc.gov.uk/en/content/cms/legislation/cc_act_08/cc_act_08.aspx

DECC (2010a). 2050 Pathways Analysis. Department of Energy and Climate Change. www.decc.gov.uk First published July 2010 © Crown Copyright. URN 10D/764.

DECC (2010b). *Updated Energy and Emission Projections*. URN 10D/510.

DECC (2011). UK Renewable Energy Roadmap. Accessed July 2011 from http://www.decc.gov.uk/assets/decc/11/meeting-energy-demand/renewable-energy/2167-uk-renewable-energy-roadmap.pdf

DECC (2011). Comprehensive Review Phase 1: Consultation on Feed-In Tarriffs For Solar PV. Retrieved January 2012 from: http://www.decc.gov.uk/en/content/cms/consultations/fits_comp_rev1/fits_comp_rev1.aspx

DECC (2012). Feed-In Tarriff Appeal: Statement by DECC Spokesperson. Retrieved January 2012 from: http://www.decc.gov.uk/en/content/cms/news/fits_appeal/fits_appeal.aspx

DEFRA (2009). Perturbed Physics Ensemble. Retreived December 2011 from http://ukclimateprojections.defra.gov.uk/content/view/933/690/

DeLaquil, P., Awerbuch, S., Stroup, K. (2005). A Portfolio-Risk Analysis of Electricity Supply Options in the Commonwealth of Virginia. Prepared for by the Chesapeake Climate Action Network.

DUKES (2010) Digest of United Kingdom energy statistics. Retrieved March 2011, from http://www.decc.gov.uk/en/content/cms/statistics/publications/dukes/dukes.aspx

Doherty, R., Outhred, H. & O'Malley, M., (2006). Establishing the Role That Wind Generation May Have in Future Generation Portfolios. *IEEE Transactions on Power Systems*, 21(3), 1415-1422. Available at: http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=1664979.

Dudziak G., Simmons J., Irvine I., (2009). Marine Energy Supply Chain Survey. Scottish Government – Marine Energy Group. Conducted by Sgurr Energy. Accessed July 2011: http://www.cambridge-resource-economics.co.uk/MEG%20Supply%20Chain%20Survey%20Report.pdf

Duncan, N. (2012) Mapping Scotland's Hydropower Resource. The University of Edinburgh. PhD Thesis.

EPA (2012). Climate Change – Greenhouse Gas Emissions. Carbon Dioxide. U.S. Environmental Protection Agency. Retrieved January 2012: http://www.epa.gov/climatechange/emissions/co2.html

European Commission. (2010). A Technology Roadmap – for the communication on Investing in the Development of Low Carbon Technologies (Set-Plan). Retrieved March 2011, from http://ec.europa.eu/energy/technology/set_plan/doc/2009_comm_investing_development_low_carbon_technologies_roadmap.pdf

European Photovoltaic Industry Association (EPIA), (2010a). Set For 2020. Solar Photovoltaic Electricity: A Mainstream Power Source in Europe by 2020. Retrieved March 2011, from http://www.setfor2020.eu/

European Photovoltaic Industry Association (EPIA), (2010b). *Solar Europe Industry Initiative Implementation Plan* 2010-2012.

ETI (2010). Marine Energy Technology Roadmap. Energy Technologies Institute and UK Energy Research Centre.

Feng, Y. and Tavner, P.J. and Long, H. (2010). Early experiences with UK Round 1 offshore wind farms. *Proceedings of the Institution of Civil Engineers : energy*., 163 (4). pp. 167-181.

Florke, M., Barlund, I., and Teichert, E. (2010) Future changes of freshwater needs in European power plants, Manage. Environ. Qual., 22, 89–104, doi:10.1108/14777831111098507, 2010.

Garg, H.P., Prakash, J. (2000). Solar Energy Fundamentals and Applications. First Revised Edition. ISBN 0-07-463631.

Greis, S.; Schulz, J. and Müller, U. (2009): Water Management of a Thermal Power Plant – A Site Specific Approach Concerning Climate Change, in: Troccoli, A. (ed.): *Weather and Climate Risk Management for the Energy Sector*, NATO Science for Peace and Security. Series C: Environmental Security, Springer, Dordrecht.

Grubb, M., Butler, L., Twomey, P., (2006). Diversity and security in UK electricity generation: The influence of low-carbon objectives. *Energy Policy*, 34(18), 4050-4062. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0301421505002442.

Hansen, J., Ruedy, R. & Sato, M.,(2010) Global surface temperature change. *Rev. Geophys*, 1-29. Available at: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.188.7662&rep=rep1&type=pdf

Harrison, G. P., Whittington, H. W. and Wallace, A. R. (2003) ‘Climate change impacts on financial risk in hydropower projects’, *IEEE Trans. Power Systems*, **18** (4), 1324-30
Harrison, G. P. and Wallace, A. R. (2005) ‘Climate sensitivity of marine energy’, *Renewable Energy*, **30** (12), 1801-17

Harrison, G. P., Wallace A. R. (2005) Sensitivity of wave energy to climate change. *IEEE Transactions on Energy Conversion*, 20 (4) (2005), pp. 870–877

Hawkins, S. (2012). High Resolution Reanalysis of Wind Speeds for Wind Energy Integration: Edinburgh Wind Model. The University of Edinburgh. PhD Thesis.

Heptonstall, P., (2007) A review of electricity unit cost estimates. Working Paper, December 2006, Updated May 2007. Report for UK Energy Research Centre, Reference: UKERC/WP/TPA/2007/006.

Hulme *et al.* (2001) *Climate change scenarios for the United Kingdom: the UKCIP02 Scientific report*, DEFRA.

IEA (1995) Using Pyranometers in Tests of Solar energy Converters: Step-by-step insructions. Retrieved January 2012 from, http://www.iea-shc.org/publications/downloads/task_9-using_pyranometers_in_tests_of_solar_energy_converters.pdf

IEA (2009). Solar PV Roadmap Targets. Accessed August 2011 from http://www.iea.org/papers/2009/PV_roadmap_targets_viewing.pdf

IEA. (2010a). Technology Roadmap. Solar photovoltaic energy.

IEA (2010b). Projected Costs of Generating Electricity.

IPCC (2007). Climate Change 2007: Synthesis Report. An Assessment of the Intergovernmental Panel on Climate Change. Accessed January 2012: http://www.ipcc.ch/publications_and_data/publications_ipcc_fourth_assessment_report_synthesis_report.htm

Jansen, Jaap C., (2004). Policy support for renewable energy in the European Union: A review of the regulatory framework and suggestions for adjustment, Petten: ECN-I–03-002.

Jenkins, G.J., Perry, M.C., and Prior, M.J. (2009). The climate of the United Kingdom and recent trends. Met Office Hadley Centre, Exeter, UK. Available from: http://ukclimateprojections.defra.gov.uk/images/stories/trends_pdfs/Trends.pdf

Johns, T. C. et al. (2003). Anthropogenic climate change for 1860 to 2100 simulated with the HadCM3 model under updated emissions scenarios. *Clim. Dyn*. 20, 583–612 (2003).

Jones, P. D., Kilsby, C. G., Harpham, C., Glenis, V., Burton, A. (2009), *UK Climate Projections science report: Projections of future daily climate for the UK from the Weather Generator*. University of Newcastle, UK

Kalogirou , S. (2009). Solar Energy Engineering: Processes and Systems [Hardcover]

Keeling, R. F., Piper, S. C., A. F. Bollenbacher, A. F., S. J. Walker, S. J. (2009) Carbon Dioxide Research Group. Scripps Institution of Oceanography (SIO). University of California. La Jolla, California USA 92093-0444. Retreived January 2012: http://cdiac.ornl.gov/ftp/trends/co2/maunaloa.co2

Krohn, S., Morthorst, P.-E., & Awerbuch, S. (2009). The Economics of Wind Energy, *European Wind Energy Association*, Brussels.

Li DHW, Lam TNT. (2007). Determining the optimum tilt angle and orientation for solar energy collection based on measured solar radiance data. *Int J Photoenergy 2007*; vol. Article ID 85402, 9 pages.

Lobell DB, Burke MB, Tebaldi C, Mastrandrea MD, Falcon WP, Naylor RL. (2008). Prioritizing climate change adaptation needs for food security in 2030. *Science* 319, 607–610.

Lorenzo, E. (2005) Energy Collected and Delivered by PV Modules, in Handbook of Photovoltaic Science and Engineering (eds A. Luque and S. Hegedus), *John Wiley & Sons*, Ltd, Chichester, UK. doi: 10.1002/0470014008.ch20

Lowe JA, Howard T, Pardaens A, Tinker J, Holt J, Wakelin S, Milne G, Leake J,Wolf J, Horsburgh K, Reeder T, Jenkins G, Ridley J, Dye S, Bradley S (2009) UK climate projections science report: marine and coastal projections. Met Office Hadley Centre, Exeter, UK.

Lui, B.Y.H., and Jordan, R.C. (1960). The interrelationship and characteristic distribution of direct, diffuse and total solar radiation. *Solar Energy* 4 (3): 1-19.

Mackay, E. B. L., Bahaj, A. S., Challenor, P. G. (2010a) Uncertainty in wave energy resource assessment. Part 1: historic data. *Renewable Energy*, 35 (2010), pp. 1792–1808

Mackay, E. B. L., Bahaj, A. S., Challenor, P. G. (2010) Uncertainty in wave energy resource assessment. Part 2: historic data. *Renewable Energy*, 35 (2010b), pp. 1809–1819

Manwell, J. F., McGowan, J. G., Rogers, A. L. (2002). *Wind Energy Explained: Theory, Design and Application.* New York:Wiley.

Martínez-Lozano, J. A., Tena, F. and Onrubia, J. E., (1984). The historical evolution of the Ångström formula and its modifications: review and bibliography. Agric. For. Meteorol. 33, pp. 109–128.

McLoughlin, E., Bazilian, M. (2006). Application of Portfolio Analysis to the Irish Electricity Generating Mix in 2020. Working Paper. Sustainable Energy Ireland.

Met Office, Hadley Centre. (1999). Climate prediction model: HadCM3: Hadley Centre Coupled Model version 3. Availabe at http://www.metoffice.gov.uk/research/modelling-systems/unified-model/climate-models/hadcm3

Met Office (2009a). UKCP09: Gridded Observation Data Sets. 25 km Gridded Data. Sunshine Duration Hours. Retrieved October 2009, from

http://www.metoffice.gov.uk/climatechange/science/monitoring/ukcp09/download/index.html

Met Office (2006). MIDAS Land Surface Stations data (1853-current). British Atmospheric Data Centre. Retrieved October 2009, from

Met Office, Hadley Centre. (2008). HadRM3-PPE-UK Model Data, [Internet]. NCAS British Atmospheric Data Centre. Retrieved September 2009, from http://badc.nerc.ac.uk/view/badc.nerc.ac.uk__ATOM__dataent_12178667495226008

Met Office (2011). Met Office Surface Data Users Guide. Retrieved December 2011, from http://badc.nerc.ac.uk/data/surface/ukmo_guide.html

Mott MacDonald (2010) *UK Electricity Generation Costs Update*. Department of Energy & Climate Change, London.

Murphy, J. M., *et al.* (2009), UK climate projections science report: Climate Change Projections, Hadley Cent., Met Off., Exeter, U. K.

OFGEM, (2010). Feed-In Tariff Installation Report Dec 2010. Retrieved March 2011, from http://www.ofgem.gov.uk/Sustainability/Environment/fits/Pages/fits.aspx

Pan, Z., Segal, M., Arritt, R.W., Takle, E. S. (2004) 'On the potential change in solar radiation over the US due to increases of atmospheric greenhouse gases', *Renewable Energy*, **29** (11), 1923-8

Pelamis (2008). Retrieved from http://www.pelamiswave.com/

Pereira de Lucena, A. F., Szklo, A. S., Schaeffer, R., Dutra, R. M. (2010). The vulnerability of wind power to climate change in Brazil *Renew Energy*, 35 (2010), pp. 904–912

Perry, M. and Hollis, D. (2005a), The generation of monthly gridded datasets for a range of climatic variables over the UK. *International Journal of Climatology*, 25: 1041–1054. doi: 10.1002/joc.1161

Perry, M.C., Hollis, D.M., (2005b). The development of a new set of longterm average climate averages for the UK. *Int J Climatol*, 25, 1023-1039.

Phillips, J. L., Cox, S. D., Henderson, A. R., Gill, J. P. (2010). Wake effects within and between large wind projects: The challenge of scal, density and neighbours – onshore and offshore. GL Garrad Hassan. Retrieved from http://www.gl-garradhassan.com/assets/downloads/1067bt58c_%28ewec2010_wakes_paper%29_-_FINAL.pdf

Pierson, W. J., and Moskowitz, L. (1964). A proposed spectral form for fully developed

wind seas based on the similarity theory of A. A. Kitaigorodskii, *J. Geophys. Res*., vol. 69, pp. 5181–5190.

Poyry (2008). *Compliance Costs for Meeting the 20% Renewable Energy Target in 2020.* A report to The Department for Business, Enterprise and Regulatory Reform, URN:08/757, available at: http://www.decc.gov.uk/publications/

PriceWaterHouseCoopers, (2010). On the brink of a bright future? Insights on the UK solar photovoltaic market.

Pryor, S. C., Barthelmie, R. J., Kjellstrom, E. (2005a) 'Potential climate change impact on wind energy resources in northern Europe: Analyses using a regional climate model', *Climate Dynamics*, **25**, 815-835.

Pryor, S. C., Barthelmie, R. J. (2005b). Climate change impacts on wind speeds and wind energy density in Northern Europe: empirical downscaling of multiple AOGCMs. *Climate Res* 29:183–98.

Pryor, S. C., Barthelmie, R. J. (2009). Climate change impacts on wind energy: a review. *Renewable and Sustainable Energy Reviews*, 14 pp. 430–437

Randall, D. A., and Coauthors, (2007) Climate models and their evaluation. Climate Change 2007: The Physical Science Basis, *Contribution of Working Group I to the Fourth*

Assessment Report of the Intergovernmental Panel on Climate Change, S. Solomon et al., Eds., Cambridge University Press, 589–662.

Reeve D, Chen Y, Pan S, Magar V, Simmonds D, Zacharioudaki A (2011) An investigation of the impacts of climate change on wave energy generation: the wave Hub, Cornwall, UK. *Renewable Energy* 36:2404–2413

Renewable UK. Formerly BWEA. (2011a). Onshore Wind Farm Statistics. Retrieved March 2011, from http://www.bwea.com/statistics/

Renewable UK (2011b). UK Wind Energy Database. Accessed from www.bwea.com/ukwed/index.asp

Renewable UK (2011c). The Economics of Wind Energy. Retrieved December 2011 from http://www.bwea.com/ref/econ.html

Roques, F. A., Newbery, D. M., Nuttall, W. J. (2006). "Fuel mix diversification incentives in liberalised electricity markets: a Mean-Variance Portfolio Theory Approach." Electricity Policy Research Group Working Paper, Cambridge.

Roques, F., Hiroux, C. & Saguan, M., (2010). Optimal wind power deployment in Europe—A portfolio approach. *Energy Policy*, 38(7), 3245-3256. Available at: http://dx.doi.org/10.1016/j.enpol.2009.07.048.

SET for 2020. (2009). Solar Photovoltaic Electricity – a Mainstream Power Source in Europe by 2020 (Executive Summary), European Photovoltaic Industry Association. www.setfor2020.eu.

Sexton, D. M. H., Murphy, J., (2010a). UKCP09: Probabilistic projections of wind speed. Hadley Cent., Met Off., Exeter, U. K. Retrieved June 2011, from http://ukclimateprojections.defra.gov.uk/content/view/1202/500/

Sexton, D. M. H., Murphy, J., (2010b). UKCP09: Probabilistic projections of wind speed. UKCP09 additional product. Met Office Hadley Centre, Exeter. Retrieved July 2011 from http://ukclimateprojections.defra.gov.uk/images/stories/Tech_notes/UKCP09_prob_wind.pdf

Shankleman, J. (2012). DECC lodges appeal against High Court solar feed-in tariff ruling. Retrieved January 2012 from http://www.businessgreen.com/bg/news/2135300/decc-lodges-appeal-court-solar-feed-tariff-ruling

Sharpe ,W. (1964)" Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk." Journal of Finance, September 1964, pp. 425-442.

Sinke, W. C., *et al.* (2007) "A Strategic Research Agenda for Photovoltaic Solar Energy Technology", European Photovoltaic Technology Platform, *Office for Official Publications of the European Union*, Luxembourg, ISBN 978-92-79-05523-2.

Skea, J., (2010). Valuing diversity in energy supply. *Energy Policy*, 38(7), 3608-3621. Available at: http://linkinghub.elsevier.com/retrieve/pii/S0301421510001199.

Solar Access (2011). Accessed from www.solaraccess.co.uk

Stirling, A., (1994). Diversity and ignorance in electricity supply investment. *Energy Policy* 22, 195–216.

Suehrcke, H. (2000). On the relationship between duration of sunshine and solar radiation on the earth's surface: Ångström's equation revisited. *Solar Energy* 68 5 (2000), pp. 417–425.

Sukhatme, S. P. (1996). Solar Energy. Principles of Thermal Collection and Storage. Second Edition. ISBN 0-07-462453-9.

Šúri, M., Hofierka, J. (2004). A New GIS-based solar radiation model and its application for photovoltaic assessments. *Transactions in GIS*, 8 2 (2004), pp. 175–190.

Šúri, M. Huld, T, A. Dunlop, E, D. (2005). PV-GIS: a web-based solar radiation database for the calculation of PV potential in Europe, *International Journal of Sustainable Energy*, 2005, 24, 2, 55

Šúri, M. Huld, T, A. Dunlop, E, D. Ossenbrink, H A. (2007). Potential of solar electricity generation in the European Union member states and candidate countries. *Solar Energy* 81 (2007) 1295-1305).

Šúri, M. Remund, J. Cebecauer, T. Dumortier, D. Wald, L. Huld, T. Blanc, P. (2008) *Proceeding of the EUROSUN 2008*, 1st International Conference on Solar Heating, Cooling and Buildings, Lisbon, Portugal, 7 – 10 October 2008.

Sunpower (2010). Sunpower 315 Solar Panel datasheet. Retreived October 2011 from http://pdf.archiexpo.com/pdf/sunpower/315-solar-panel-datasheet/Show/54500-12402-_2.html

The Crown Estate (2011a). Offshore wind Energy – Rounds 1 and 2. Retrieved March 2011 from http://www.thecrownestate.co.uk/rounds-one-two

The Crown Estate (2011b). Offshore wind Energy - Round 3. Retrieved March 2011 from http://www.thecrownestate.co.uk/round3

The Crown Estate (2011c). Offshore wind Energy – Wind farms in Scottish Waters. Retrieved March 2011 from http://www.thecrownestate.co.uk/scottish-offshore-wind

The Crown Estate (2011d). Offshore Wind Energy. Accessed December 2011 from www.thecrownestate.co.uk/energy/

The Renewable Energy Foundation (REF) (2011). Renewables Obligation Generators Database. Retrieved March 2011 from http://www.ref.org.uk/roc-generators/

Troen I, Petersen EL. (1989). European Wind Atlas. Risø National Laboratory: Roskilde.

Twidell, J. Weir, T. (2006) Renewable energy resources (Second edition), Taylor & Francis.

UKCIP (2002). UK Climate Impact Programme. UKCIP02 UK Climate Projections. Available at http://www.ukcip.org.uk/ukcp09/ukcip02/

UKCIP (2009). UK Climate Impact Programme. UKCP09 UK Climate Projections. Available at http://www.ukcip.org.uk/ukcp09/

UKERC (2009). The UKERC Energy 2050 Project. Available from: http://www.ukerc.ac.uk/Downloads/PDF/U/UKERCEnergy2050/0906UKERC2050.pdf

http://badc.nerc.ac.uk/data/ukmo-midas

UNFCCC. (2012). Definition of climate change. Accessed January 2012 from http://unfccc.int/files/documentation/text/html/list_search.php?what=keywords&val=&valan=a&anf=0&id=10

Usher, W. & Strachan N. (2010), UK MARKAL Modelling - Examining Decarbonisation Pathways in the 2020s on the Way to Meeting the 2050 Emissions Target. Accessed October 2011: http://downloads.theccc.org.uk.s3.amazonaws.com/4th%20Budget/CCC%20MARKAL%20Final%20Report%20-%20UCL%20Nov10.pdf

Vestas (2011). Vestas V90 3.0 MW Wind Turbine Brochure. Retrieved March 2011, from http://www.vestas.com/en/media/brochures.aspx

Vicuna, S. et al., (2007) Climate change impacts on high elevation hydropower generation in California's Sierra Nevada: a case study in the Upper American River. *Climatic Change*, 87(S1), 123-137. Available at: http://www.springerlink.com/index/10.1007/s10584-007-9365-x.

Wang, G., (2005). Agricultural drought in a future climate: results from 15 global climate models participating in the IPCC 4th assessment. *Climate Dynamics*, 25(7-8), 739-753. Available at: http://www.springerlink.com/index/10.1007/s00382-005-0057-9.

Wang, X. L., Zwiers, F.W., Swail, V.R. (2004) 'North Atlantic Ocean wave climate change scenarios for the Twenty-First Century', *J. Climate*. **17**, 2368-83.

Wave Hub (2011) Wave Hub Project website. Available at: http://www.wavehub.co.uk

White, B. (2007). A Mean-Variance Portfolio Optimization of California's Generation Mix to 2020: Achieving California's 22 Percent Renewable Portfolio Standard Goal. Prepared for California Energy Commission.

Winskel, M., Markusson, N., Moran, B. & Jeffrey, H. (2009). *Decarbonising the UK Energy System: Accelerated Development of Low Carbon Energy Supply Technologies*. UKERC Energy 2050 Research Report No. 2 UK Energy Research Centre, London

Woolf, D. K., Challenor, P. G. and Cotton, P. D. (2002) 'Variability and predictability of the North Atlantic wave climate', *J. Geophysical Res*. **109** (C10), 3145-58

Appendices

Appendix A

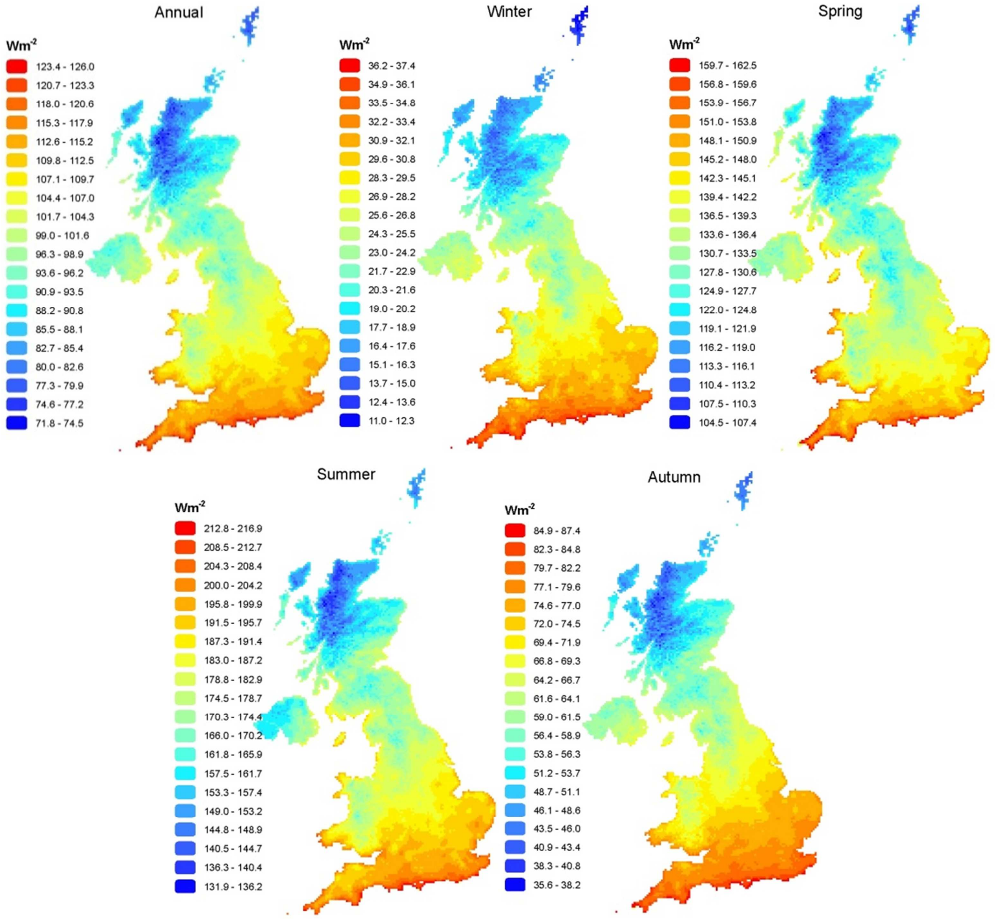


Figure A-1: Average solar radiation resource on horizontal plane over the baseline time period.

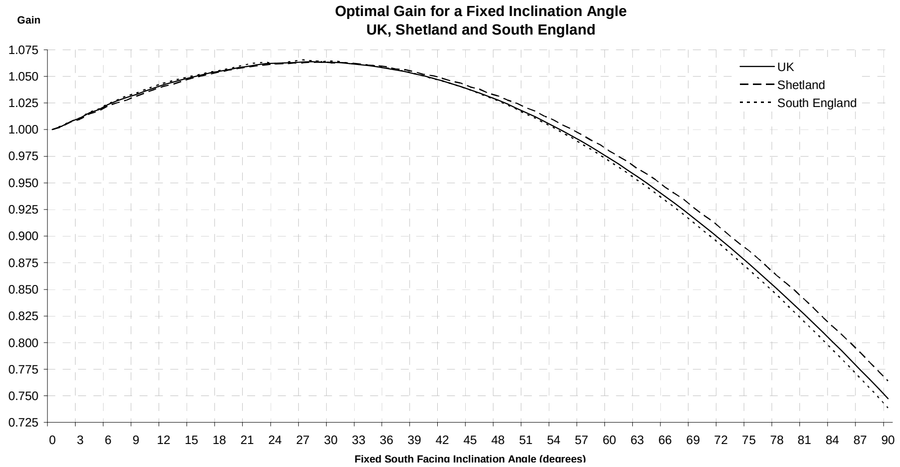


Figure A-2: Gains for different permanently fixed inclination angles at extreme latitudes of the UK and average UK.

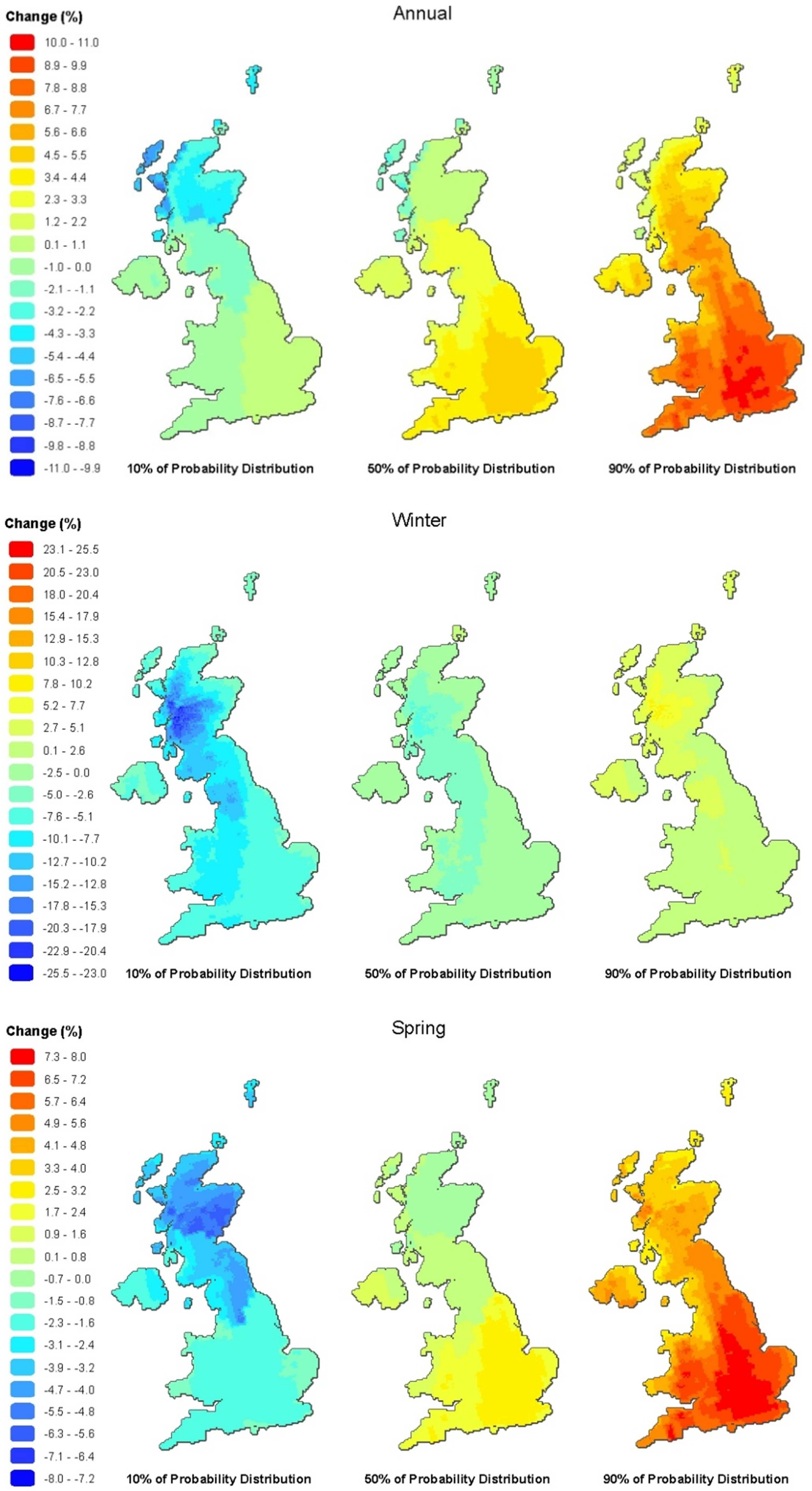


Figure A-3: Solar percentage changes from baseline for 2050s medium emissions scenario 50% (10%, 90%)

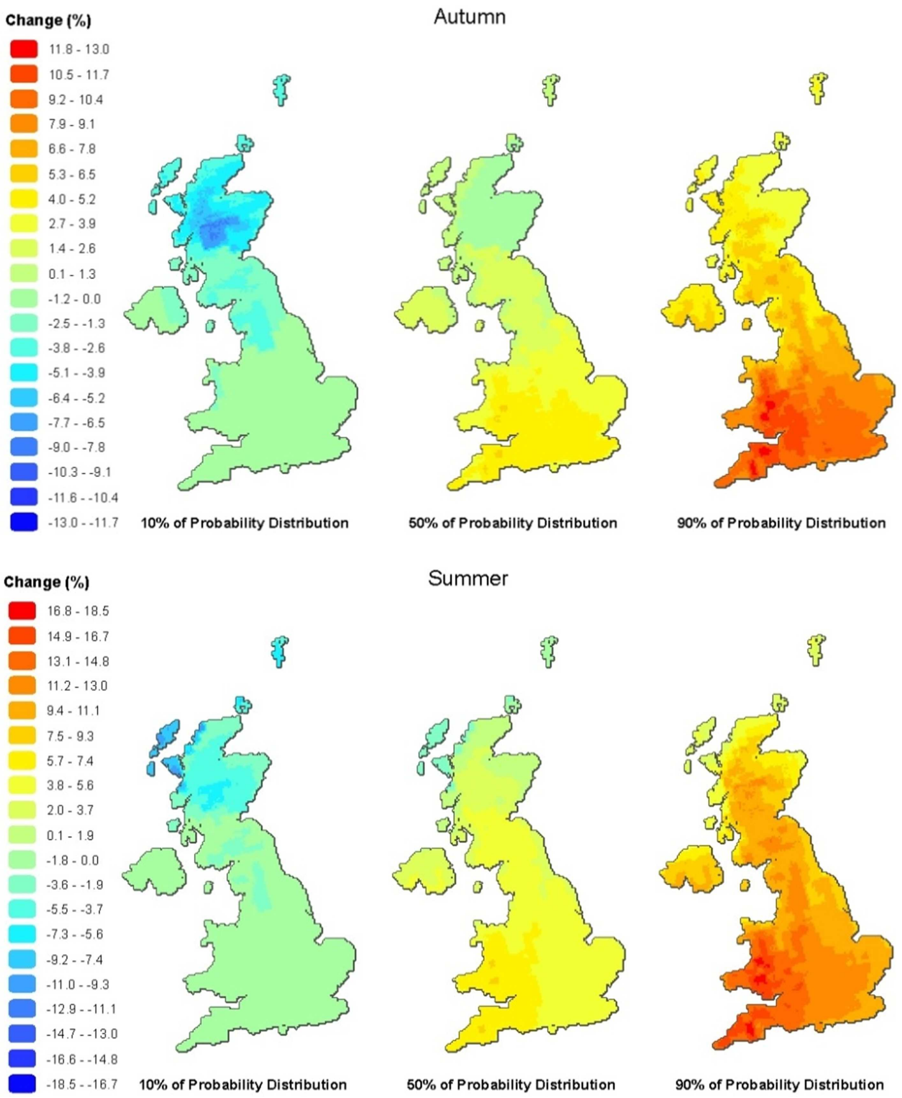


Figure A-3 (continued): Solar percentage changes from baseline for 2050s medium emissions scenario 50% (10%, 90%)

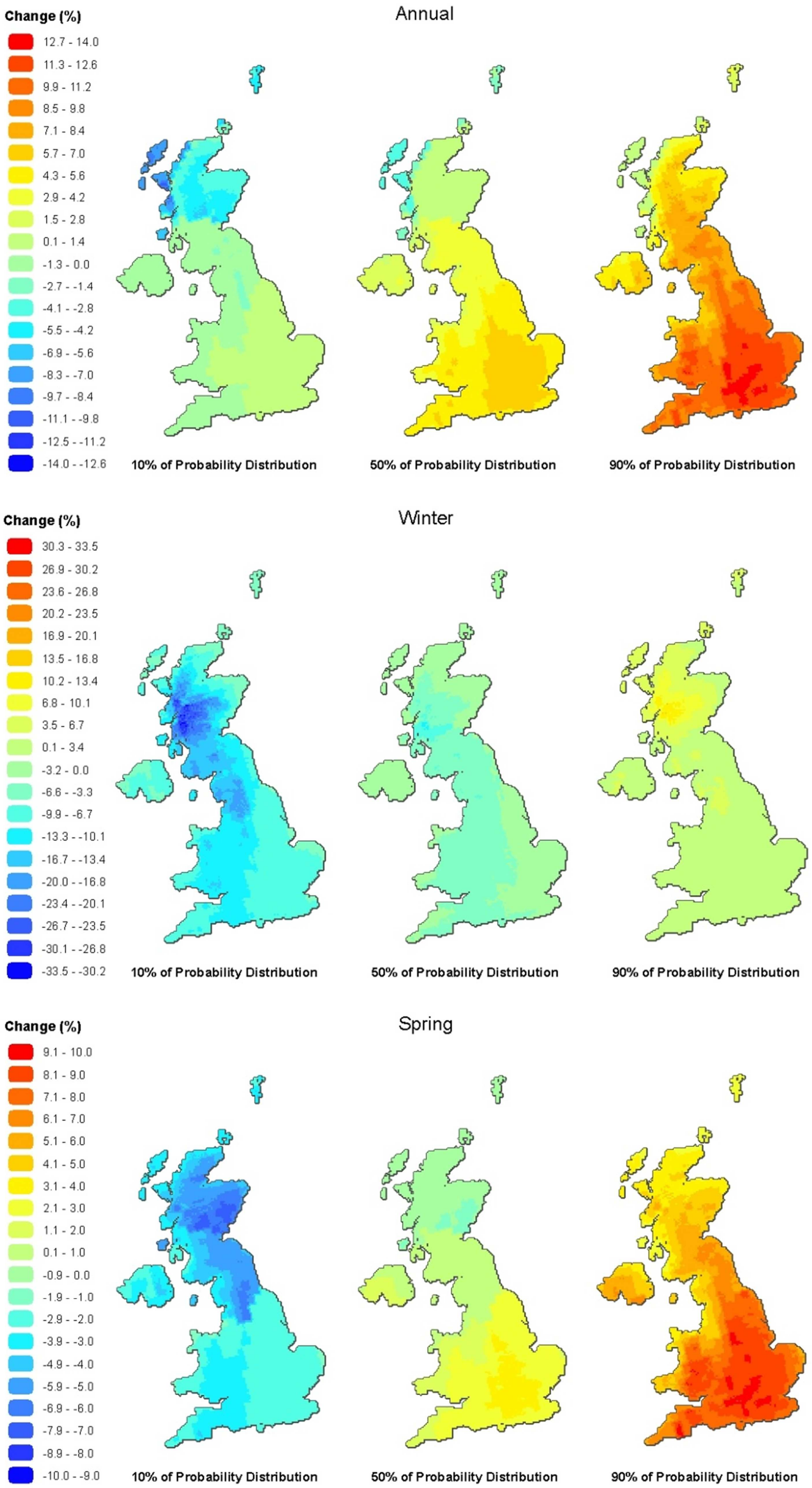
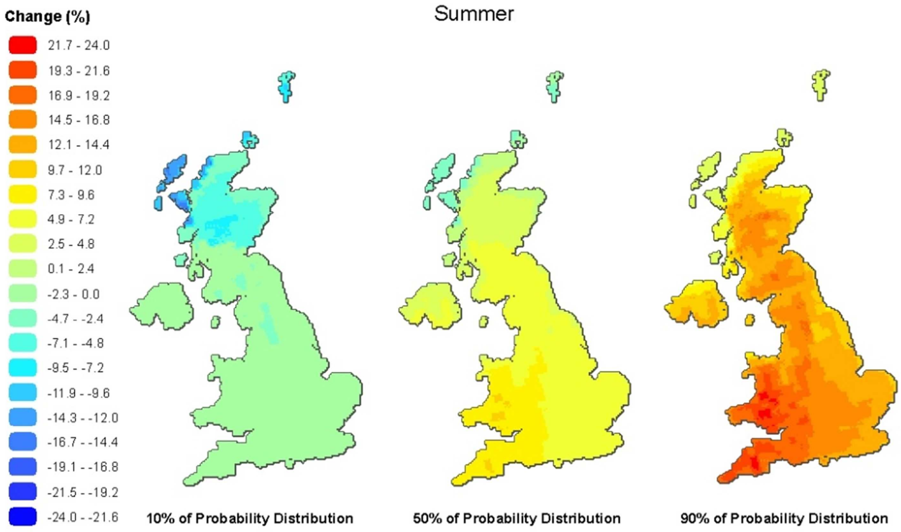


Figure A-4: Solar percentage changes from baseline for 2080s medium emissions scenario 50% (10%, 90%)



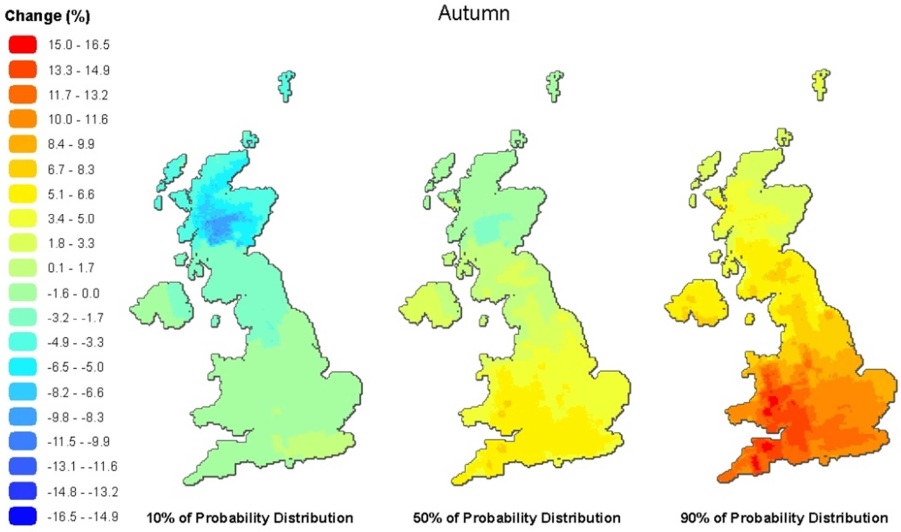


Figure A-4 (continued): Solar percentage changes from baseline for 2080s medium emissions scenario 50% (10%, 90%)

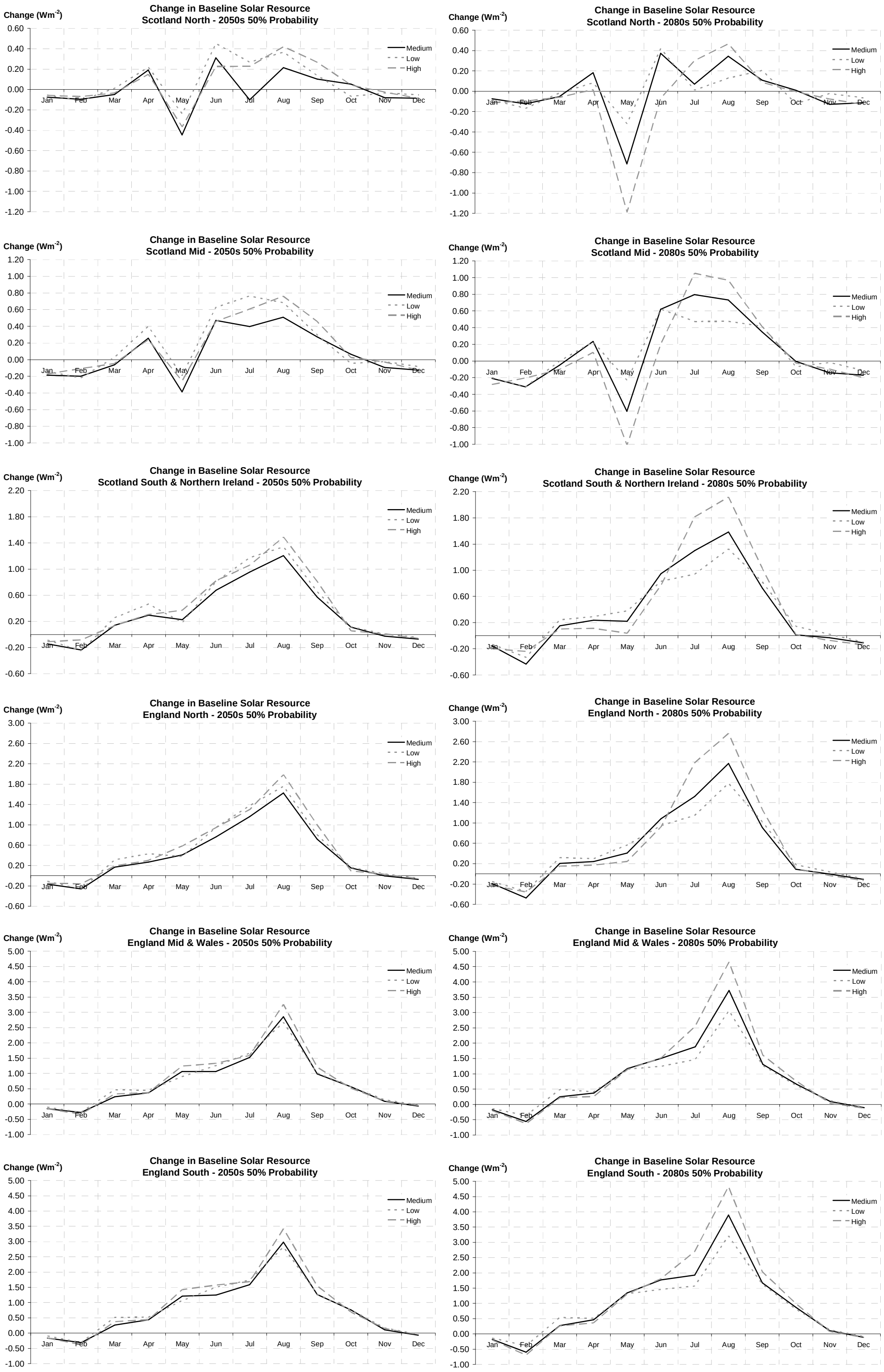


Figure A-6: Regional Average Change from Baseline in Wm^{-2} for the 2050s and 2080s

Appendix B

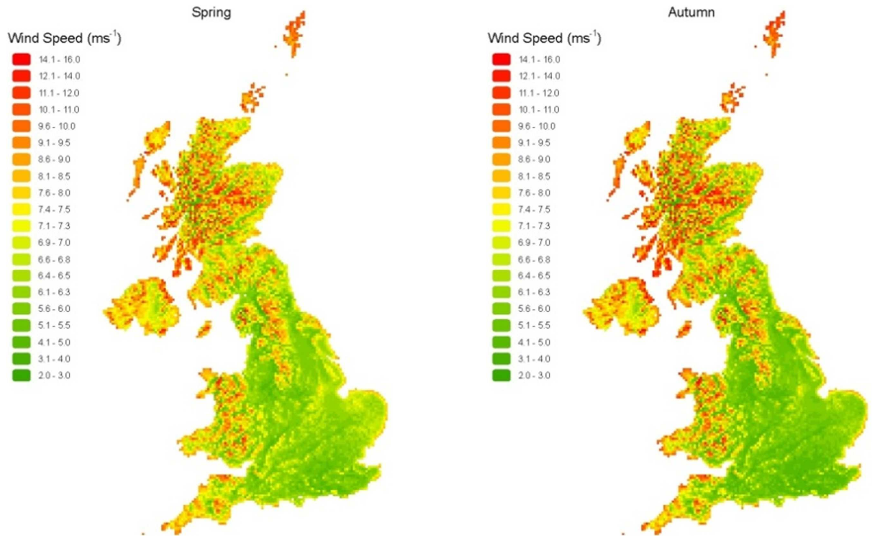


Figure B-1: UK baseline onshore average wind speed resource at 80m height for Spring and Summer

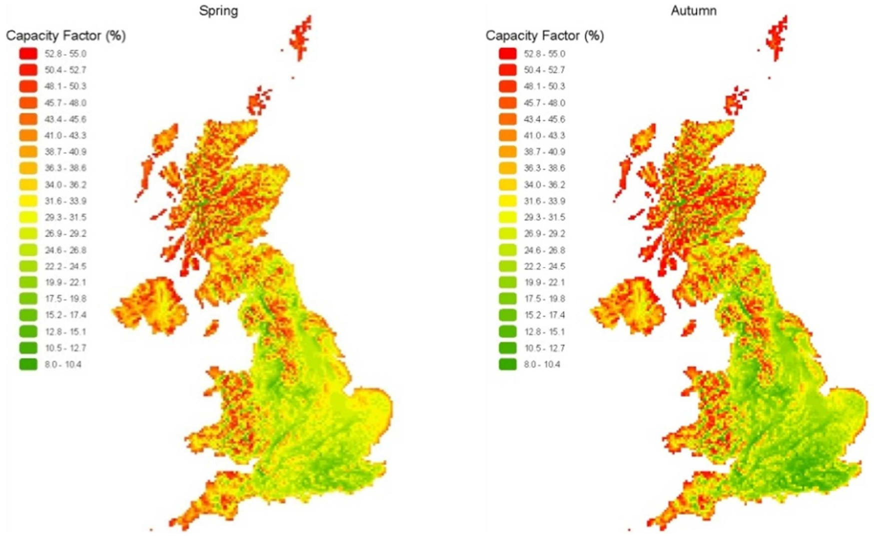


Figure B-2: Seasonal onshore baseline capacity factors for spring and summer

Figure B-3 shows the percentage of time above cut out for winter and summer months. Winter months, due to the higher wind speeds are more likely to have a higher proportion of time above cut out. Many of the locations most affected are exposed hilly or mountainous locations; these are largely in the Highlands of Scotland.

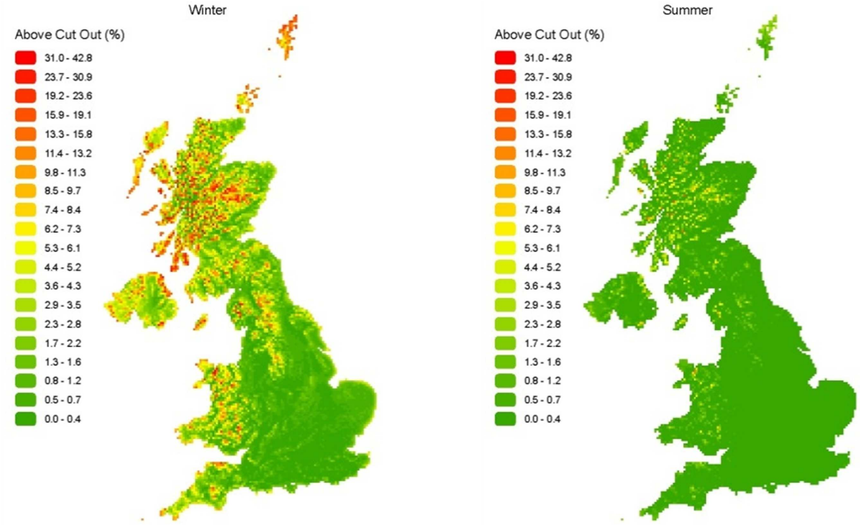


Figure B-3: Percentage of time in above cut out state for winter and summer months.

Figure B-4 shows the percentage of time below cut in, where wind speeds are too low for the turbine to generate (below 3 m/s). It shows that summer months, with least wind resource have the locations with highest below cut in values. Lowlands in the South East and as well as sheltered locations in mountainous locations are mostly affected

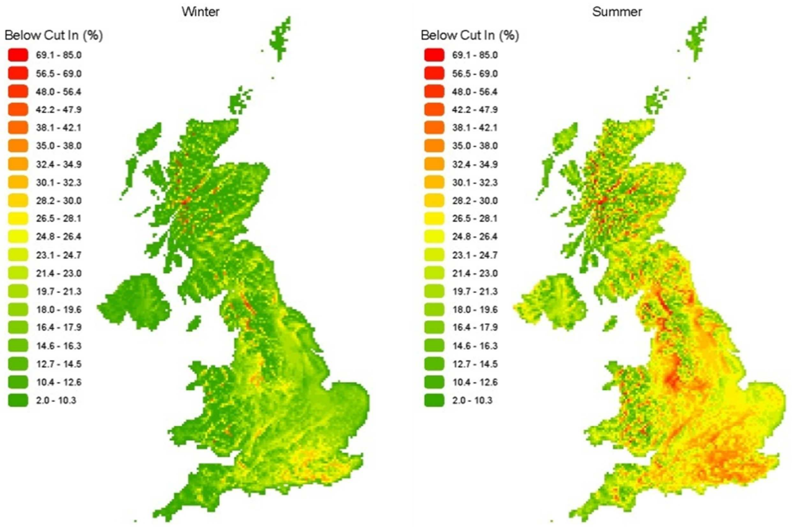


Figure B-4: Percentage of time in below cut in state for winter and summer months.

Figures B-6 to B-8 show the percentage of time at rating, below rating and generating. At rating is when the turbine is running at its maximum capacity, in the case of the Vestas V90 this is 3 MW. Below rated shows the percentage of time when generating at less than full capacity, which is when the output is on the actual curve of the power curve. Generating shows the percentage of time when generating, the value is equal to the sum of the values of below rating and at rating. It clearly shows that wind turbines operate for quite substantial proportions of the year.

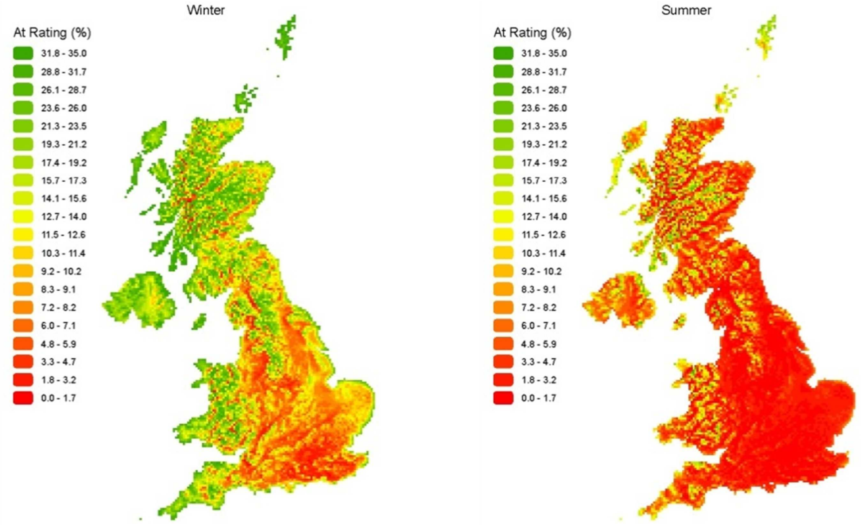


Figure B-6: Percentage of time at full rating for winter and summer months.

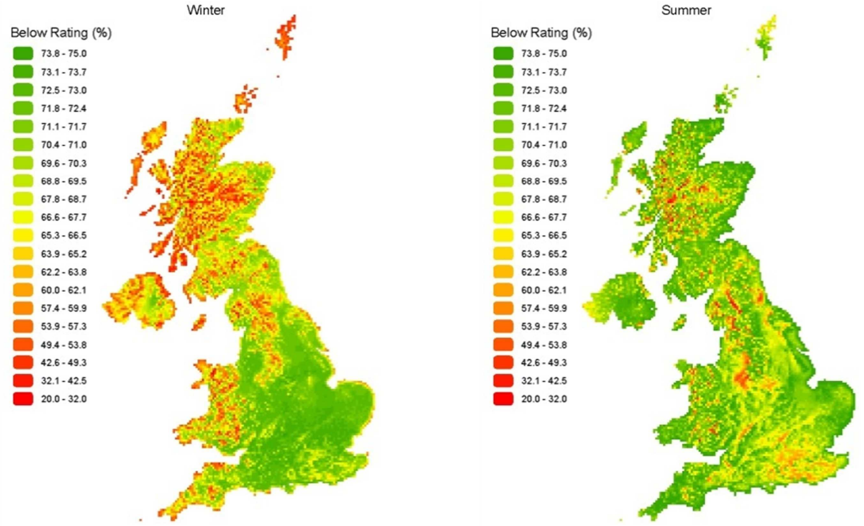


Figure B-7: Percentage of time below rating for winter and summer months.

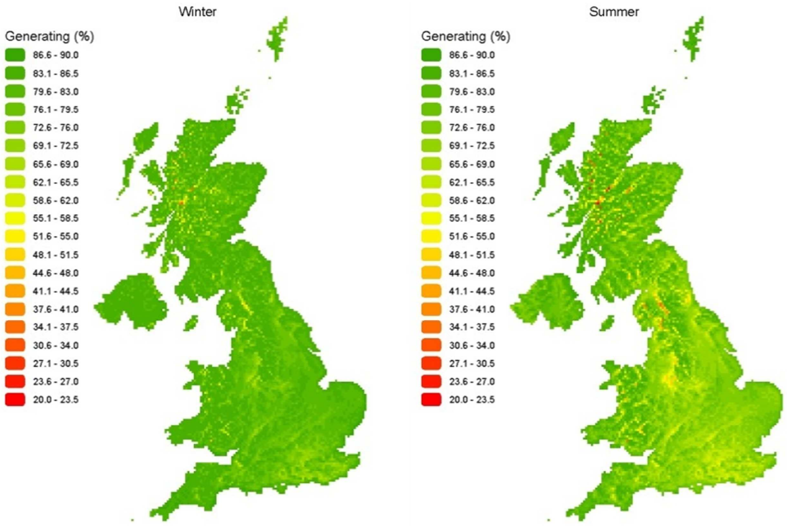


Figure B-8: Percentage of time generating for winter and summer months.

Figure B-9 shows the change in proportion of time in the ‘above cut-out’ state for winter months. It can be seen that there are some locations showing significant reduction of time in the ‘above cut-out’ state. The locations are all relatively windy locations that have significant reduction in wind speeds projected for the 2050s and 2080s. Summer months are not shown as there were not any locations with any significant ‘above cut-out’ change due to relatively lower wind speeds in the summer months.

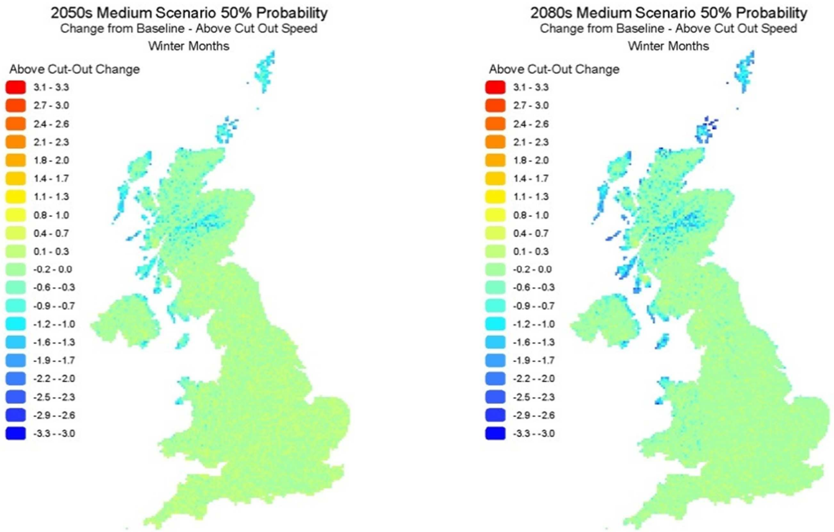


Figure B-9: Projected Winter above cut-out change for the 2050s and 2080s medium scenario

Figure B-10 shows the projected change in the proportion of time in the ‘at rating’ state for 2080s winter and summer months. The 2050s show the same trend but to a lesser degree. Summer months do not have as large a reduction as Winter months and is partly due to the baseline ‘at rating’ proportions being smaller in the summer months as well as lower wind speed reductions in the Summer months. The Winter months show more areas with significant reduction, especially in North and North West coastal areas in Scotland and the northerly islands (Shetland and Orkney).

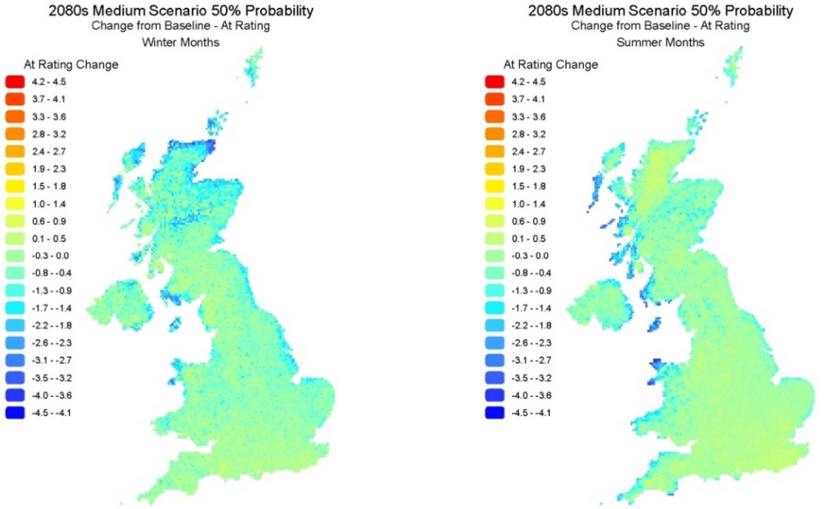


Figure B-10: Projected Winter and Summer at rating change for the 2080s medium scenario

Figure B-11 shows the projected change in the proportion of time in ‘generating’ state for state for 2080s winter and summer months. The 2050s show the same trend but to a lesser scale. In summer months the vast majority of change is a shift from ‘generating’ to ‘below cut-in’ due to reduced wind speeds. In winter months a small proportion of the change is also a shift from ‘generating’ to ‘above cut out’ due to some wind speed increases.

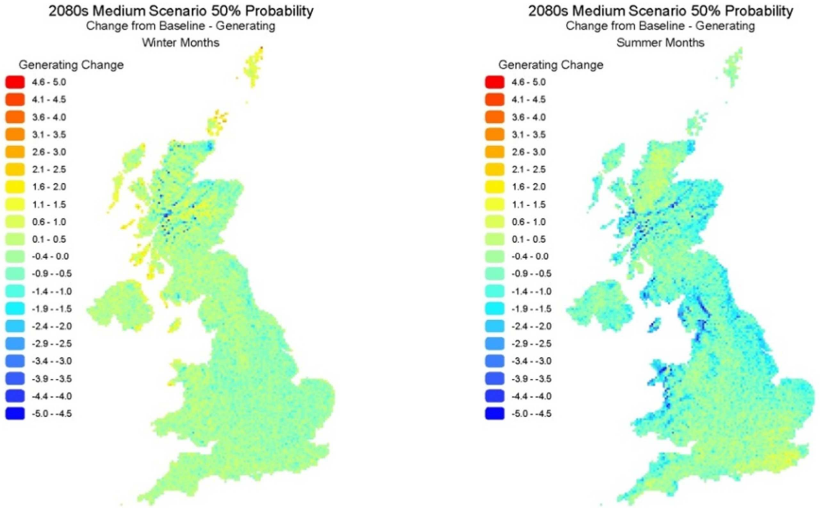


Figure B-11: Projected Winter and Summer at rating change for the 2080s medium scenario

Figure B-12 shows the projected change in the proportion of time 'generating' state for 2080s winter and summer months. Most locations are showing an increase of 0.1 to 2% of time in the below cut-in state due to the largely lower wind speeds. The locations in red are mainly sheltered locations such as valleys with low baseline wind speeds.

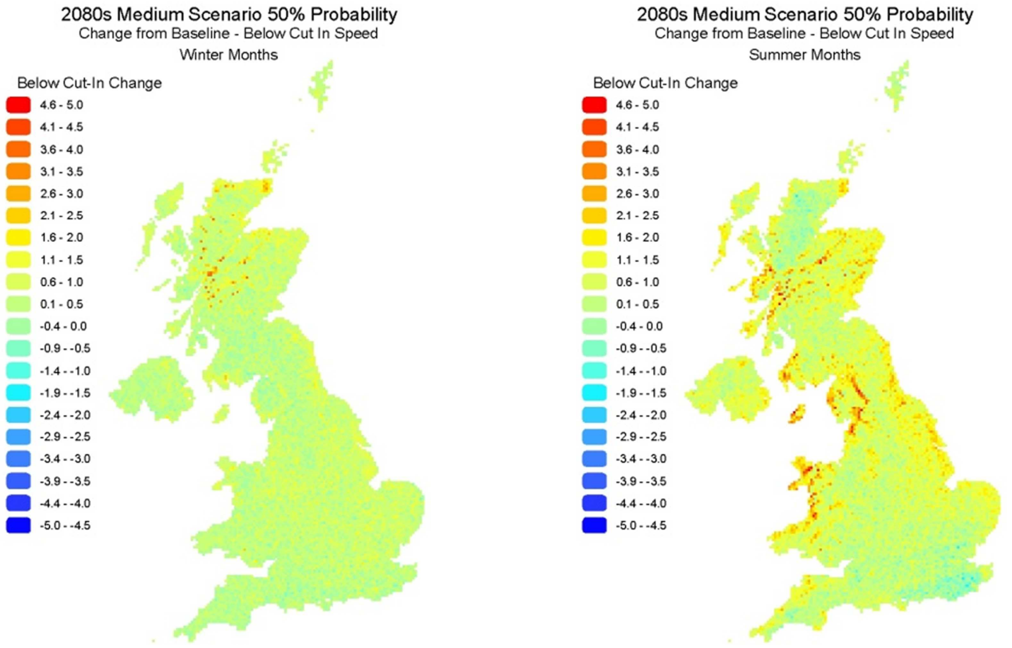


Figure B-12: Projected Winter and Summer below cut-in change for the 2080s medium scenario

Table B-1 shows the weighted average capacity factor change values for all included onshore wind farm locations for the 2050s and 2080s.

	Projected Aggregate Capacity Factor Change From Baseline (%) – Assuming No Losses												
	ANN	**JAN**	**FEB**	**MAR**	**APR**	**MAY**	**JUN**	**JUL**	**AUG**	**SEP**	**OCT**	**NOV**	**DEC**
Baseline	**41.9**	**49.8**	**48.2**	**48.7**	**42.0**	**37.9**	**36.4**	**31.6**	**30.9**	**40.8**	**43.3**	**46.4**	**47.9**
2050s 10%	39.6	47.5	46.0	46.7	40.3	35.2	33.7	28.4	26.2	37.5	41.8	45.2	46.9
2050s 50%	**41.7**	**49.4**	**47.3**	**48.4**	**41.6**	**37.3**	**36.8**	**31.7**	**29.3**	**39.7**	**43.3**	**47.0**	**48.5**
2050s 90%	43.7	51.0	48.7	49.8	42.7	39.6	39.6	35.0	32.4	41.8	44.8	48.7	49.9
2080s 10%	39.1	47.4	45.9	46.5	39.5	34.6	33.2	27.4	24.8	36.7	42.02	45.4	46.2
2080s 50%	**41.3**	**48.9**	**47.5**	**47.7**	**41.2**	**37.2**	**36.4**	**30.8**	**28.6**	**39.1**	**43.7**	**47.0**	**48.1**
2080s 90%	43.4	50.3	48.9	48.7	42.7	39.7	39.5	34.0	32.2	41.6	45.2	48.5	49.6

Table B-1: Projected Aggregate Capacity Factor Change from Baseline - assuming no losses

Appendix C

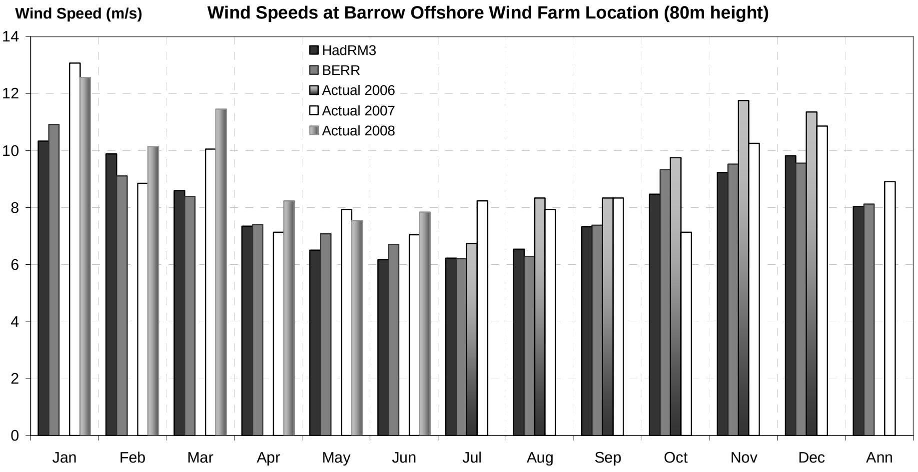


Figure C-1: Wind Speed Comparison of Barrow Offshore Wind Farm Location

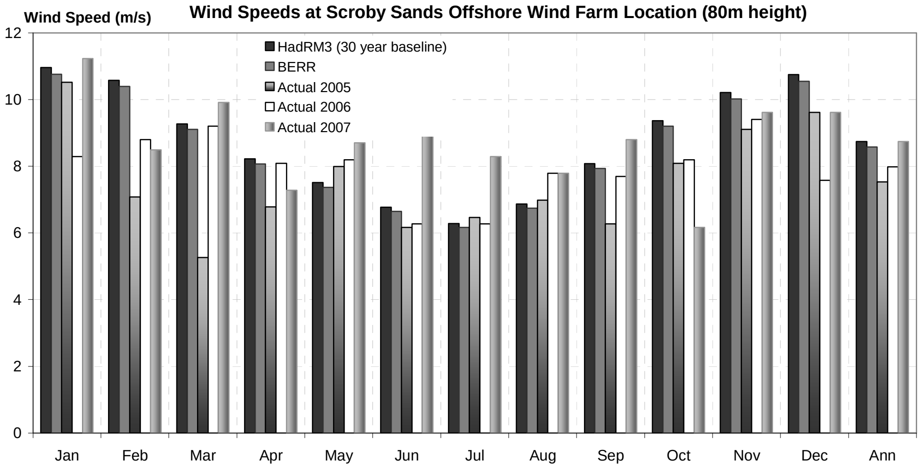


Figure C-2: Wind Speed Comparison of Scroby Sands Offshore Wind Farm Location

C.1 Barrow Offshore Wind Farm

The Barrow Offshore Wind Farm has been operational since September 2006. It comprises 30 Vestas V90 3 MW turbines at a hub height of 75 m, which makes it very similar to the generic parameters used to create the modelled baseline energy values. The Barrow Wind Farm anticipates annual energy production to be 305 GWh (BOW 2008). The modelled baseline energy data estimates the value at 336.5 GWh but assumes 100% technical availability and does not include any losses.

Figure C-3 shows the location of Barrow Wind Farm within the baseline gridded energy model showing capacity factor. Each cell is 25km^2. The cell which contains Barrow (X) and 5 other adjacent cells are highlighted.

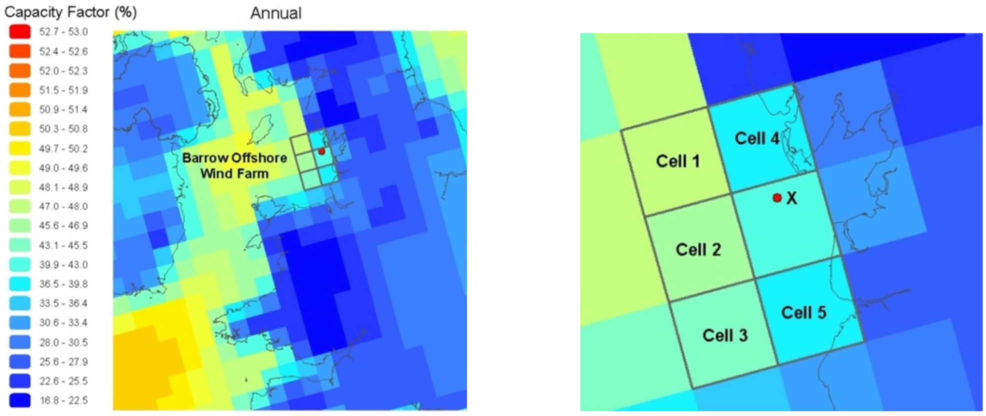


Figure C-3: Location of Barrow Offshore Farm on 25km baseline gridded capacity factor model.

Figure C-4 shows the capacity factor actual average (Real Avg) and model average for the Barrow site. The actual average is averaged over three operational years and the spread over those years (2008-2010) is indicated by bars. The model average is the value at location X average (Model Avg). There are too few samples of measured data for the average to show any long term characteristics but the modelled baseline values are indicative of the actual values; the 3 years characteristics approach the 30 year modelled baseline characteristics. There have been substantial maintenance issues resulting in reduced output, especially in 2006 and 2007 and those particular years have not been included in Figure C-4. All gearboxes were exchanged, pitch systems were modified and generator bearings and rotor cables had to be changed to different types. Much of the high level of maintenance work was further hampered and delayed by excessive bad weather conditions (BERR 2004-2009).

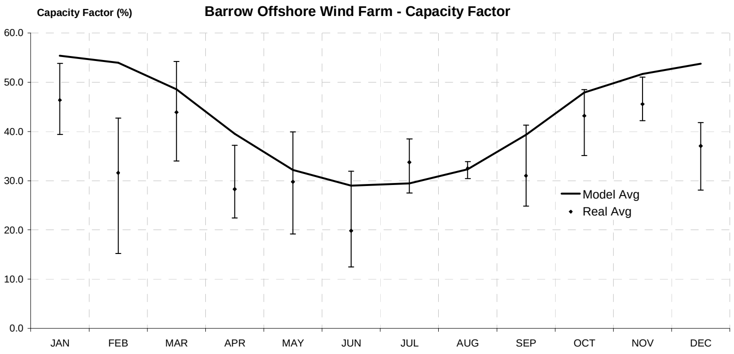


Figure C-4: Actual capacity factor data and modelled baseline capacity factor (REF 2011).

C.2 Scroby Sands Offshore Wind Farm

Scroby Sands was commissioned in 2004 and is one of the first offshore wind farms in the UK. It comprises of 30 V80 2 MW Vestas turbines at a hub height of 70 m. Figure C-5 shows the location of the wind farm, the grid cell it falls within and adjacent cells.

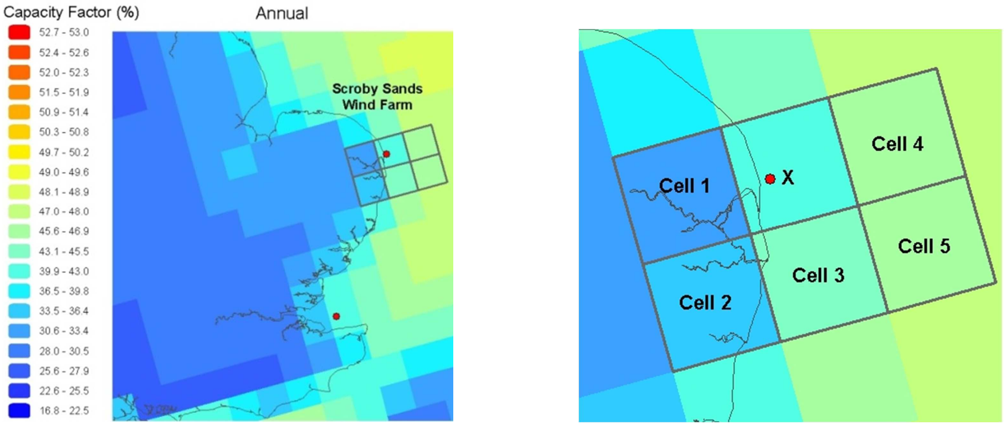


Figure C-5: Location of Scroby Sands Offshore Farm on 25km baseline gridded capacity factor model.

The modelled average capacity factor for the location and actual observed average capacity factor over 5 years of operation with spread are shown in Figure C-6. There is again too few years of real historical capacity factor data to perform any accurate comparisons of real to modelled baseline capacity factor. Scroby Sands has also suffered from a high level of operational issues that have hampered output.

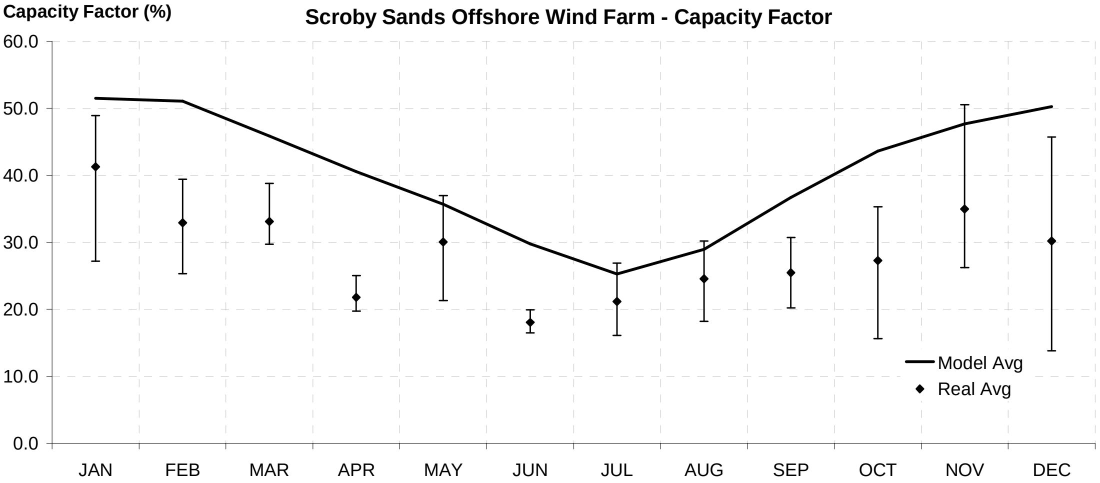


Figure C-6: Actual capacity factor data and modelled baseline capacity factor

C.3 Kentish Flats Offshore Wind Farm

Kentish Flats has been in operation since late 2005 and consists of 30 Vestas V90 3.0 MW wind turbines with a hub height of 70m. The location is shown in Figure C-7 and modelled and real capacity factor values are shown in Figure C-8. Kentish Flats has also suffered from many operational issues that have affected the availability over early years of operation.

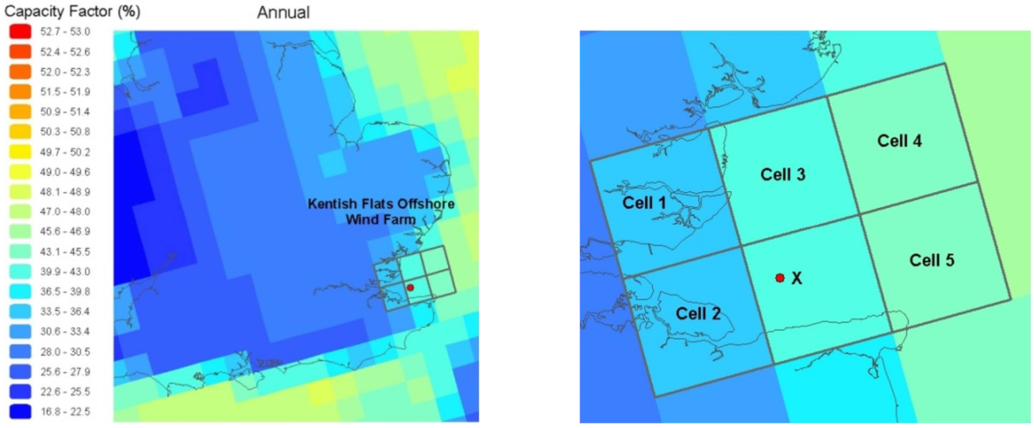


Figure C-7: Location of Kentish Flats Offshore Farm on 25km baseline gridded capacity factor model.

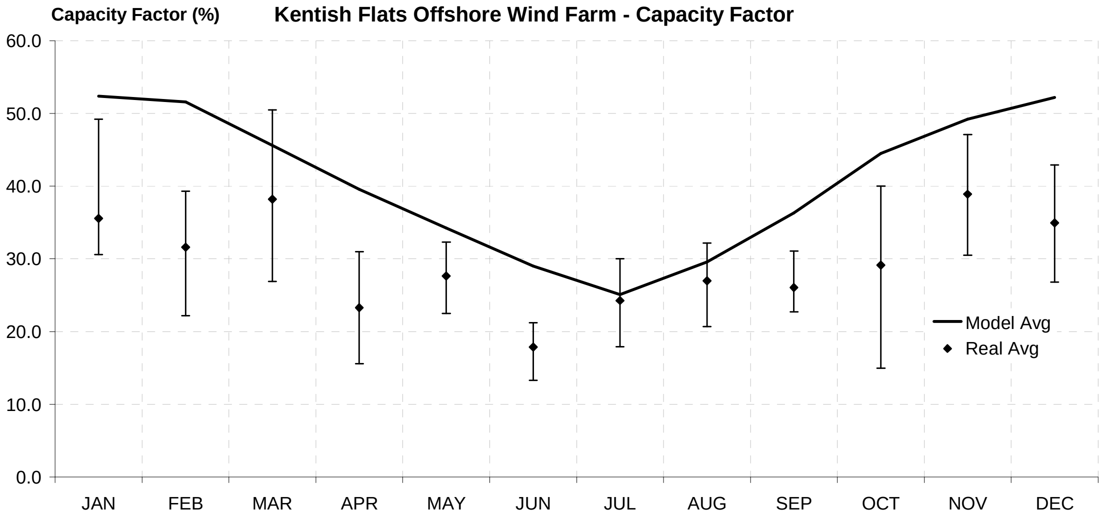


Figure C-8: Actual capacity factor data and modelled baseline capacity factor

Name	MW	Capacity Factors (%)												
		ANN	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
ROUND 1														
Barrow	90	42.7	55.4	54.0	48.5	39.5	32.2	29.0	29.4	32.3	39.3	47.9	51.7	53.7
Burbo Bank	90	37.9	50.5	49.6	44.2	36.3	29.8	25.3	24.1	26.9	33.4	41.1	45.2	48.4
Burbo Bank Ext’	234	37.9	50.5	49.6	44.2	36.3	29.8	25.3	24.1	26.9	33.4	41.1	45.2	48.4
Gunfleet Sands I	108	41.0	52.8	51.7	45.9	40.1	34.9	29.0	25.3	29.8	36.8	44.8	49.2	51.9
Kentish Flats	90	40.8	52.4	51.6	45.6	39.6	34.2	29.0	25.1	29.6	36.3	44.5	49.2	52.2
Kentish Flats II	51	40.8	52.4	51.6	45.6	39.6	34.2	29.0	25.1	29.6	36.3	44.5	49.2	52.2
Lynn/Inner Dowsing	194.4	41.4	54.2	53.7	48.8	41.9	35.3	27.8	23.1	27.2	36.6	45.2	50.4	53.1
North Hoyle	60	40.9	53.4	52.5	47.9	39.5	31.9	27.3	26.2	29.4	36.7	44.9	49.0	51.6
Ormonde	150	42.7	55.4	54.0	48.5	39.5	32.2	29.0	29.4	32.3	39.3	47.9	51.7	53.7
Rhyl flats	90	40.5	52.7	51.8	47.4	39.7	32.4	27.8	26.2	28.8	36.0	44.0	48.0	50.8
Robin Rigg	180	41.0	52.4	51.7	47.8	41.1	33.3	28.1	26.6	28.6	37.0	45.7	49.1	50.8
Scroby Sands	60	40.6	51.5	51.1	45.8	40.6	35.7	29.7	25.2	28.9	36.7	43.6	47.7	50.2
Teesside	90	41.1	53.6	53.1	48.4	40.9	34.3	26.8	23.4	27.7	36.9	45.8	49.8	52.2

Table C-1: Baseline Capacity factors for Round 1 wind farm locations

Name	MW	Capacity Factors (%)												
		ANN	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
ROUND 2														
Docking Shoal	500	45.1	56.4	56.0	52.4	45.3	38.9	31.2	26.0	31.4	42.1	50.8	54.6	56.1
Dudgeon	560	46.7	56.7	56.2	52.9	46.7	40.8	33.4	28.6	34.8	45.5	53.0	55.5	56.5
Greater Gabbard	504	45.8	56.0	55.4	50.7	44.8	39.3	33.9	29.7	34.7	43.3	51.2	54.5	55.8
Galloper	504	45.8	56.0	55.4	50.7	44.8	39.3	33.9	29.7	34.7	43.3	51.2	54.5	55.8
Gunfleet Sands II	64.8	41.0	52.8	51.7	45.9	40.1	34.9	29.0	25.3	29.8	36.8	44.8	49.2	51.9
Gwynt Y Mor	750	40.5	52.7	51.8	47.4	39.7	32.4	27.8	26.2	28.8	36.0	44.0	48.0	50.8
Humber Gateway	300	44.9	56.6	56.1	52.2	45.5	38.9	31.0	25.9	30.5	41.1	50.3	54.4	55.9
Lincs	270	41.4	54.2	53.7	48.8	41.9	35.3	27.8	23.1	27.2	36.6	45.2	50.4	53.1
London Array	630	45.1	55.7	55.1	49.8	44.0	38.4	32.8	28.7	34.1	42.2	50.6	54.3	55.5
London ArrayII	370	45.1	55.7	55.1	49.8	44.0	38.4	32.8	28.7	34.1	42.2	50.6	54.3	55.5
Race Bank	620	45.1	56.4	56.0	52.4	45.3	38.9	31.2	26.0	31.4	42.1	50.8	54.6	56.1
Sheringham Shoal	317	46.7	56.7	56.2	52.9	46.7	40.8	33.4	28.6	34.8	45.5	53.0	55.5	56.5
Thanet	300	45.4	56.0	55.2	50.3	44.2	38.7	33.1	29.2	34.7	42.8	50.6	54.2	56.1
Thanet II	147	45.4	56.0	55.2	50.3	44.2	38.7	33.1	29.2	34.7	42.8	50.6	54.2	56.1
Triton Knoll	1200	45.6	56.8	56.4	53.2	46.3	39.7	31.8	26.6	31.5	42.5	51.3	55.2	56.2
Walney	183.6	42.7	55.4	54.0	48.5	39.5	32.2	29.0	29.4	32.3	39.3	47.9	51.7	53.7
Walney Extension	183.6	42.7	55.4	54.0	48.5	39.5	32.2	29.0	29.4	32.3	39.3	47.9	51.7	53.7
West Duddon	500	42.7	55.4	54.0	48.5	39.5	32.2	29.0	29.4	32.3	39.3	47.9	51.7	53.7
Westernmost Rough	240	45.4	56.5	56.1	53.0	46.1	39.6	32.0	26.7	31.5	41.9	51.2	54.6	56.0

Table C-2: Baseline Capacity factors for Round 2 wind farm locations

Name	MW	Capacity Factors (%)												
		ANN	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
ROUND 3														
Bristol Channel	1500	44.4	55.3	54.7	51.3	45.0	37.8	33.0	29.7	31.4	38.7	48.8	52.8	54.6
Dogger Bank	9000	48.7	56.7	56.6	54.7	49.6	43.3	37.3	33.6	38.4	48.1	54.1	56.0	56.5
Firth of Forth	3500	47.4	56.7	56.4	54.1	48.0	40.8	34.5	31.2	36.0	46.0	53.4	55.5	56.5
Hastings	600	43.8	54.0	53.0	48.9	44.0	38.6	34.0	30.9	33.5	38.3	46.3	51.0	53.2
Hornsea	4000	47.4	56.8	56.6	54.0	48.0	42.0	35.1	30.6	35.2	45.8	53.0	55.6	56.6
Irish Sea	4200	47.6	56.5	56.6	55.0	49.1	41.4	34.9	32.0	35.5	45.0	53.1	55.7	56.4
Norfolk	7200	47.1	56.3	55.9	52.1	46.6	41.4	35.6	31.2	36.5	45.7	52.5	55.2	56.2
West Isle of Wight	900	47.2	56.6	56.3	54.0	48.9	41.8	36.2	32.2	34.8	41.9	51.5	55.4	56.4
Moray Firth	1300	47.6	56.7	56.6	55.2	50.1	42.5	34.7	30.3	34.3	45.1	53.1	55.5	56.5

Table C-3: Baseline Capacity factors for Round 3 wind farm locations

Name	MW	Capacity Factors (%)												
		ANN	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
SCOTTISH														
Argyll	1500	50.1	56.3	56.7	56.1	52.0	45.0	39.2	36.8	40.3	50.0	55.4	56.8	56.8
Beatrice Demo	10	46.0	56.7	56.5	54.8	48.9	40.6	32.0	27.1	30.8	42.4	51.8	54.7	56.4
Beatrice	920	47.6	56.7	56.6	55.2	50.1	42.5	34.7	30.3	34.3	45.1	53.1	55.5	56.5
Forth	280	46.6	56.5	56.2	53.5	46.7	39.5	33.0	29.8	34.9	45.0	52.7	55.1	56.2
Inch Cape	905	46.6	56.5	56.2	53.5	46.7	39.5	33.0	29.8	34.9	45.0	52.7	55.1	56.2
Islay	680	50.4	56.2	56.5	56.1	52.1	45.5	39.6	38.0	41.8	50.4	55.7	56.6	56.7
Kintyre	378	47.8	56.3	56.2	54.5	48.8	41.7	35.5	33.7	36.8	45.9	53.3	55.1	56.1
Neart na Gaoithe	300	46.6	56.5	56.2	53.5	46.7	39.5	33.0	29.8	34.9	45.0	52.7	55.1	56.2
Solway Firth	300	41.8	53.1	52.5	48.8	42.0	34.1	29.1	27.7	29.7	37.8	46.3	49.6	51.3
Wigtown Bay	280	47.6	56.8	56.3	54.4	48.7	41.2	35.0	33.1	35.5	45.0	53.2	55.6	56.5
OTHERS														
Blyth	4	41.4	52.8	52.7	48.4	41.3	34.8	28.2	24.6	28.9	37.8	46.0	49.2	51.5
Tunes Plateau	250	48.6	56.3	56.4	55.0	49.6	43.1	36.7	34.8	38.4	47.1	53.9	55.6	56.2
Aberdeen	150	46.8	56.4	56.3	53.9	47.6	40.5	34.0	30.2	34.0	44.5	52.7	55.0	56.2

Table C-4: Baseline Capacity factors for Scottish Exclusivity and ‘other’ wind farm locations

Name	MW	Change in Capacity Factor from Baseline - 2050 Medium Scenario (50% Probability)												
		ANN	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
Barrow	90	-0.66	-0.27	-0.92	-1.11	-0.64	-0.72	1.61	-0.37	-3.82	-3.00	-0.27	0.97	0.69
Burbo Bank	90	-0.78	-0.40	-1.36	-1.28	-0.98	-1.04	1.35	-0.34	-3.53	-3.29	-0.51	1.17	0.91
Burbo Bank Ext’	234	-0.66	-0.27	-0.92	-1.11	-0.64	-0.72	1.61	-0.37	-3.82	-3.00	-0.27	0.97	0.69
Gunfleet Sands I	108	-0.65	0.43	-1.12	-0.71	-0.36	-1.03	-0.06	-0.55	-2.19	-3.27	-1.03	1.44	0.61
Kentish Flats	90	-0.65	0.43	-1.12	-0.71	-0.36	-1.03	-0.06	-0.55	-2.19	-3.27	-1.03	1.44	0.61
Kentish Flats II	51	-0.65	0.43	-1.12	-0.71	-0.36	-1.03	-0.06	-0.55	-2.19	-3.27	-1.03	1.44	0.61
Lynn/Inner Dowsing	194.4	-1.12	0.04	-0.98	-1.15	-1.19	-2.05	-0.32	-0.81	-3.14	-4.22	-0.95	0.83	0.5
North Hoyle	60	-0.78	-0.40	-1.36	-1.28	-0.98	-1.04	1.35	-0.34	-3.53	-3.29	-0.51	1.17	0.91
Ormonde	150	-0.66	-0.27	-0.92	-1.11	-0.64	-0.72	1.61	-0.37	-3.82	-3.00	-0.27	0.97	0.69
Rhyl flats	90	-0.78	-0.40	-1.36	-1.28	-0.98	-1.04	1.35	-0.34	-3.53	-3.29	-0.51	1.17	0.91
Robin Rigg	180	-1.41	-0.44	-0.94	-1.42	-1.62	-2.02	-0.23	-1.57	-5.14	-3.69	-0.66	0.37	0.46
Scroby Sands	60	-0.68	0.34	-1.00	-0.62	-0.12	-1.06	0.07	-0.99	-2.32	-3.8	-0.71	1.34	0.68
Teeside	90	-0.82	-0.57	-1.74	-0.94	-1.20	-1.44	0.27	0.28	-2.76	-2.9	-0.65	0.92	0.94

Table C-5: Change in Capacity Factor from Baseline for Round 1 Wind Farm Locations - 2050s Medium Scenario with 50% Probability.

Name	MW	Change in Capacity Factor from Baseline - 2050 Medium Scenario (50% Probability)												
		ANN	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
Docking Shoal	500	-1.12	0.04	-0.98	-1.15	-1.19	-2.05	-0.32	-0.81	-3.14	-4.22	-0.95	0.83	0.5
Dudgeon	560	-0.98	-0.16	-0.62	-0.9	-0.84	-1.44	0.17	-0.6	-3.37	-3.92	-0.94	0.59	0.27
Greater Gabbard	504	-0.76	0.06	-0.68	-0.58	-0.25	-0.86	-0.3	-0.84	-2.45	-3.57	-0.85	0.92	0.27
Galloper	504	-0.76	0.06	-0.68	-0.58	-0.25	-0.86	-0.3	-0.84	-2.45	-3.57	-0.85	0.92	0.27
Gunfleet Sands II	64.8	-0.65	0.43	-1.12	-0.71	-0.36	-1.03	-0.06	-0.55	-2.19	-3.27	-1.03	1.44	0.61
Gwynt Y Mor	750	-0.78	-0.4	-1.36	-1.28	-0.98	-1.04	1.35	-0.34	-3.53	-3.29	-0.51	1.17	0.91
Humber Gateway	300	-1.06	-0.2	-0.95	-1.05	-1.11	-1.78	-0.48	-0.68	-3.28	-3.48	-0.81	0.61	0.46
Lincs	270	-1.12	0.04	-0.98	-1.15	-1.19	-2.05	-0.32	-0.81	-3.14	-4.22	-0.95	0.83	0.5
London Array	630	-0.65	0.43	-1.12	-0.71	-0.36	-1.03	-0.06	-0.55	-2.19	-3.27	-1.03	1.44	0.61
London ArrayII	370	-0.65	0.43	-1.12	-0.71	-0.36	-1.03	-0.06	-0.55	-2.19	-3.27	-1.03	1.44	0.61
Race Bank	620	-1.12	0.04	-0.98	-1.15	-1.19	-2.05	-0.32	-0.81	-3.14	-4.22	-0.95	0.83	0.50
Sheringham Shoal	317	-0.98	-0.16	-0.62	-0.90	-0.84	-1.44	0.17	-0.60	-3.37	-3.92	-0.94	0.59	0.27
Thanet	300	-0.65	0.43	-1.12	-0.71	-0.36	-1.03	-0.06	-0.55	-2.19	-3.27	-1.03	1.44	0.61
Thanet II	147	-0.65	0.43	-1.12	-0.71	-0.36	-1.03	-0.06	-0.55	-2.19	-3.27	-1.03	1.44	0.61
Triton Knoll	1200	-1.23	-0.23	-0.73	-1.26	-1.53	-2.02	-0.63	-1.04	-3.42	-4.15	-0.65	0.46	0.38
Walney I	183.6	-0.66	-0.27	-0.92	-1.11	-0.64	-0.72	1.61	-0.37	-3.82	-3.00	-0.27	0.97	0.69
Walney Extension	183.6	-0.66	-0.27	-0.92	-1.11	-0.64	-0.72	1.61	-0.37	-3.82	-3.00	-0.27	0.97	0.69
West Duddon	500	-0.66	-0.27	-0.92	-1.11	-0.64	-0.72	1.61	-0.37	-3.82	-3.00	-0.27	0.97	0.69
Westernmost Rough	240	-1.06	-0.20	-0.95	-1.05	-1.11	-1.78	-0.48	-0.68	-3.28	-3.48	-0.81	0.61	0.46

Table C-6: Change in Capacity Factor from Baseline for Round 2 Wind Farm Locations - 2050s Medium Scenario with 50% Probability.

Name	MW	Change in Capacity Factor from Baseline - 2050 Medium Scenario (50% Probability)												
ROUND 3		ANN	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
Bristol Channel	1500	-0.93	0.04	-0.76	-0.81	-0.58	-1.04	0.25	-0.48	-3.90	-3.88	-1.30	0.92	0.32
Dogger Bank	9000	-0.74	-0.02	-0.22	-0.44	-0.99	-0.97	0.44	-0.56	-3.47	-2.77	-0.43	0.26	0.24
Firth of Forth	3500	-0.68	-0.10	-0.27	-0.62	-0.86	-0.74	-0.18	-0.60	-3.35	-1.76	-0.08	0.30	0.10
Hastings	600	-0.55	0.19	-0.69	-0.72	-0.78	-0.91	0.17	0.29	-1.61	-2.57	-1.57	1.19	0.42
Hornsea	4000	-1.03	-0.05	-0.37	-0.72	-0.76	-1.63	0.01	-1.30	-3.58	-3.81	-0.66	0.39	0.10
Irish Sea	4200	-1.98	0.02	-0.32	-1.13	-1.73	-3.13	-1.45	-3.11	-6.69	-5.12	-1.21	0.11	0.02
Norfolk	7200	-0.75	0.07	-0.49	-0.51	-0.05	-0.86	0.12	-1.14	-2.81	-3.74	-0.63	0.81	0.26
West Isle of Wight	900	-1.06	0.22	-0.39	-0.74	-0.90	-1.39	-0.50	-0.58	-3.79	-3.68	-1.57	0.56	0.05
Moray Firth	1300	-1.24	-0.08	-0.50	-0.80	-1.68	-2.21	-0.63	-1.14	-3.77	-2.43	-1.04	-0.41	-0.24

Table C-7: Change in Capacity Factor from Baseline for Round 3 Wind Farm Locations - 2050s Medium Scenario with 50% Probability.

Name	MW	Change in Capacity Factor from Baseline - 2050 Medium Scenario (50% Probability)												
SCOTTISH		ANN	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
Argyll	1500	-1.14	0.42	0.01	-0.40	-0.73	-1.9	-1.09	-1.84	-4.75	-2.56	-0.51	-0.21	-0.11
Beatrice Demo	920	-1.24	-0.08	-0.50	-0.80	-1.68	-2.21	-0.63	-1.14	-3.77	-2.43	-1.04	-0.41	-0.24
Beatrice	10	-1.24	-0.08	-0.50	-0.80	-1.68	-2.21	-0.63	-1.14	-3.77	-2.43	-1.04	-0.41	-0.24
Forth	280	-1.24	-0.08	-0.50	-0.80	-1.68	-2.21	-0.63	-1.14	-3.77	-2.43	-1.04	-0.41	-0.24
Inch Cape	905	-0.68	-0.01	-0.37	-0.82	-0.90	-1.00	-0.13	-0.43	-3.23	-1.79	0.01	0.43	0.14
Islay	680	-0.99	0.44	0.26	-0.41	-1.26	-2.46	-0.46	-1.13	-4.10	-2.45	-0.40	0.03	0.01
Kintyre	378	-1.30	-0.03	-0.22	-0.93	-1.57	-2.84	-0.28	-1.16	-4.21	-3.37	-1.11	0	0.11
Neart na Gaoithe	300	-0.82	-0.35	-1.37	-1.16	-1.12	-1.32	0	0.07	-3.12	-2.45	-0.49	0.83	0.63
Solway Firth	300	-1.41	-0.44	-0.94	-1.42	-1.62	-2.02	-0.23	-1.57	-5.14	-3.69	-0.66	0.37	0.46
Wigtown Bay	280	-1.77	-0.23	-0.38	-1.15	-2.03	-2.84	-0.46	-2.57	-5.54	-4.29	-1.36	-0.14	-0.27
OTHERS														
Blyth	4	-0.82	-0.35	-1.37	-1.16	-1.12	-1.32	0	0.07	-3.12	-2.45	-0.49	0.83	0.63
Tunes Plateau	250	-1.25	0.11	-0.42	-0.90	-1.36	-3.08	-0.09	-1.04	-4.34	-3.1	-0.91	-0.08	0.19
Aberdeen	150	-0.68	-0.13	-0.60	-0.66	-0.74	-0.39	0.33	-0.75	-3.27	-1.79	-0.18	-0.03	0.07

Table C-8: Change in Capacity Factor from Baseline for Scottish Exclusive Wind Farm Locations and others - 2050s Medium Scenario with 50% Probability.

Scenario	Projected Aggregate Capacity Factor Change From Baseline (%) – Assuming No Losses												
	ANN	**JAN**	**FEB**	**MAR**	**APR**	**MAY**	**JUN**	**JUL**	**AUG**	**SEP**	**OCT**	**NOV**	**DEC**
Baseline	46.82	56.23	55.94	53.14	47.33	40.86	34.69	31.07	35.44	44.85	52.21	54.89	55.94
2050s 50%	-0.97	0.01	-0.47	-0.72	-0.88	-1.42	-0.08	-1.04	-3.67	-3.32	-0.68	0.47	0.22
2080s 50%	-1.58	-0.18	-0.59	-1.61	-1.58	-1.52	-0.99	-2.64	-5.56	-4.12	-0.39	0.34	-0.04
2050s 10%	-3.55	-0.67	-1.42	-2.36	-2.61	-4.55	-4.3	-6.94	-9.44	-6.65	-2.35	-0.73	-0.34
2050s 50%	-0.97	0.01	-0.47	-0.72	-0.88	-1.42	-0.08	-1.04	-3.67	-3.32	-0.68	0.47	0.22
2050s 90%	1.30	0.22	0.16	0.61	0.71	1.46	3.90	4.57	1.80	-0.33	0.73	1.21	0.46
2080s 10%	-4.48	-1.02	-1.69	-3.05	-4.36	-5.11	-5.72	-8.78	-11.49	-8.56	-2.30	-0.67	-0.78
2080s 50%	-1.58	-0.18	-0.59	-1.61	-1.58	-1.52	-0.99	-2.64	-5.56	-4.12	-0.39	0.34	-0.04
2080s 90%	1.01	0.18	0.13	-0.35	0.89	1.78	3.48	3.40	0.15	-0.19	1.20	1.03	0.40

Table C-9: Projected Aggregate Capacity Factor Change from Baseline - assuming no losses

Appendix D

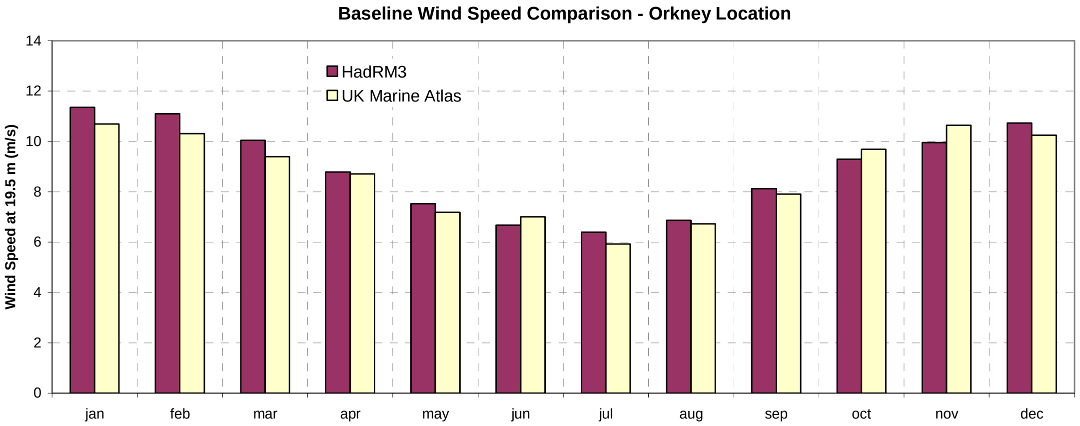

Baseline Wind Speed Comparison - Orkney Location

Figure D-1: Comparing Wind speed data for Orkney Location

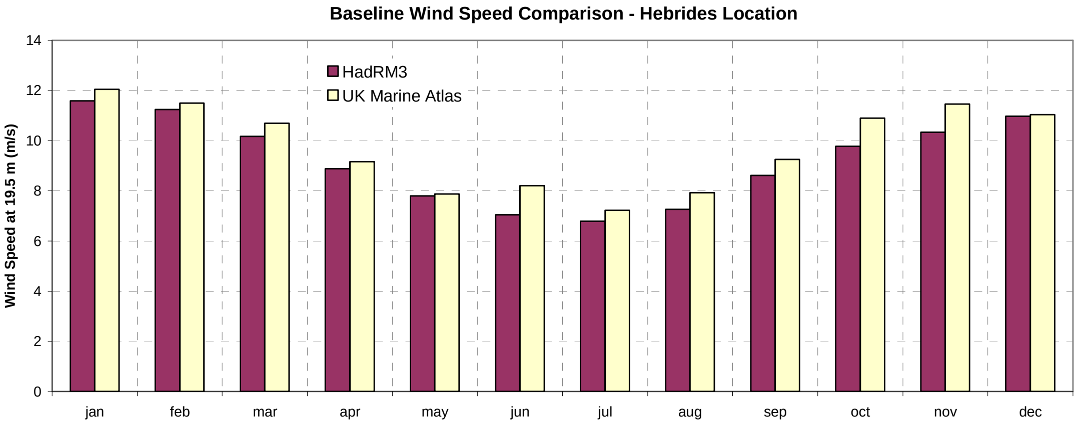

Baseline Wind Speed Comparison - Hebrides Location

Figure D-2: Comparing Wind speed data for Hebrides Location

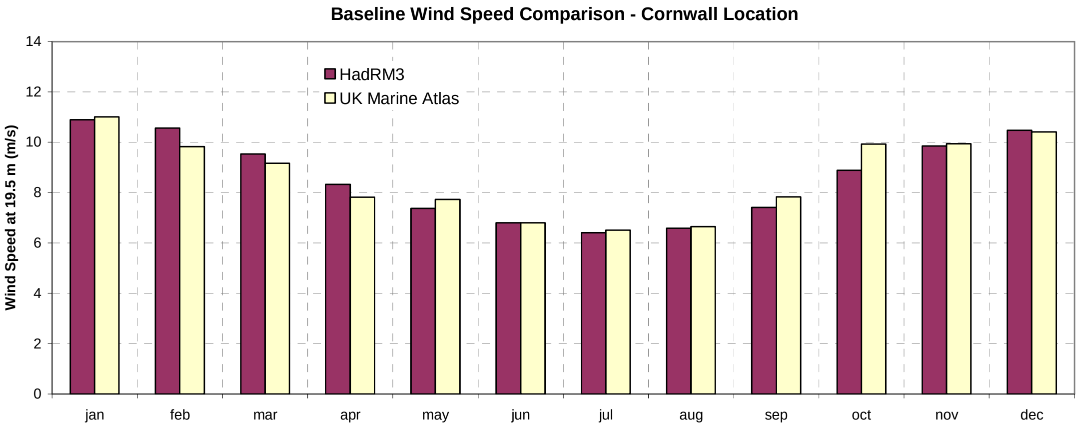

Baseline Wind Speed Comparison - Cornwall Location

Figure D-3: Comparing Wind speed data for Cornwall Location

Significant Wave Height (m)			
	BERR Actual	BERR from wind speed	HadRM3 from wind speed
Annual	1.99	2.11	2.21
January	2.79	3.07	3.46
February	2.64	2.86	3.31
March	2.23	2.38	2.71
April	1.96	2.04	2.08
May	1.58	1.39	1.53
June	1.38	1.32	1.2
July	1.15	0.94	1.1
August	1.35	1.22	1.27
September	1.72	1.68	1.78
October	2.07	2.53	2.33
November	2.61	3.04	2.67
December	2.52	2.83	3.1

Table D-1: Orkney location significant wave height (*Hs*) comparison

Significant Wave Height (m)			
	BERR Actual	BERR from wind speed	HadRM3 from wind speed
Annual	2.71	2.64	2.35
January	3.91	3.88	3.6
February	3.53	3.55	3.4
March	3.04	3.07	2.78
April	2.6	2.26	2.13
May	2.1	1.67	1.64
June	1.94	1.81	1.34
July	1.68	1.41	1.24
August	1.87	1.69	1.42
September	2.43	2.31	2
October	2.88	3.19	2.57
November	3.42	3.53	2.87
December	3.31	3.27	3.24

Table D-2: Hebrides location significant wave height (*Hs*) comparison

Significant Wave Height (m)			
	BERR Actual	BERR from wind speed	HadRM3 from wind speed
Annual	2.09	2.07	2.05
January	3.07	3.26	3.18
February	2.62	2.6	3
March	2.38	2.26	2.44
April	1.82	1.64	1.87
May	1.83	1.61	1.46
June	1.45	1.24	1.24
July	1.36	1.14	1.1
August	1.35	1.19	1.17
September	1.7	1.65	1.48
October	2.47	2.65	2.12
November	2.51	2.66	2.61
December	2.58	2.92	2.95

Table D-3: Cornwall location significant wave height (*Hs*) comparison

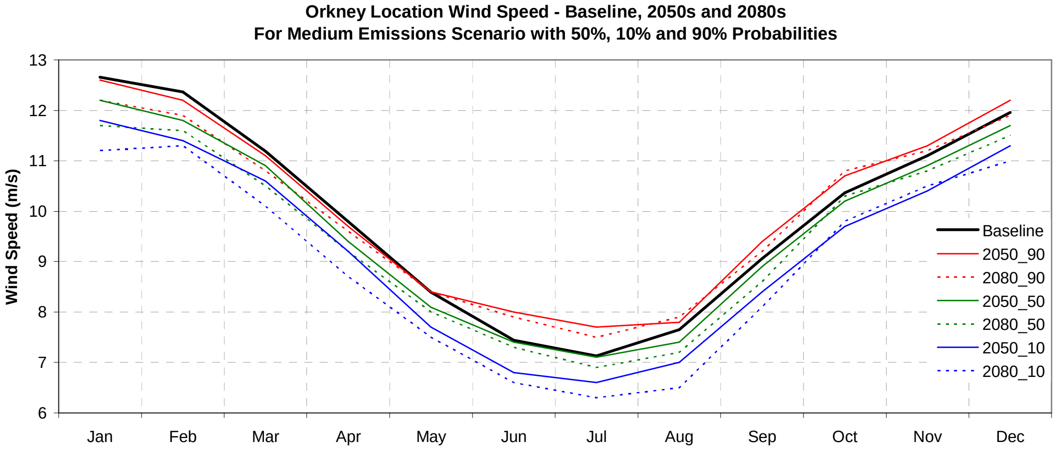


Figure D-4: Orkney location - Projected Wind Speed change from baseline

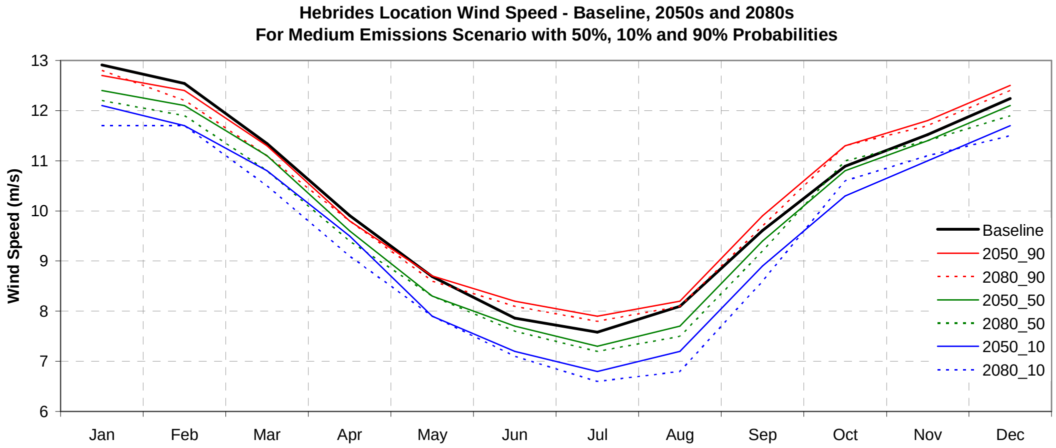


Figure D-5: Hebrides location - Projected Wind Speed change from baseline

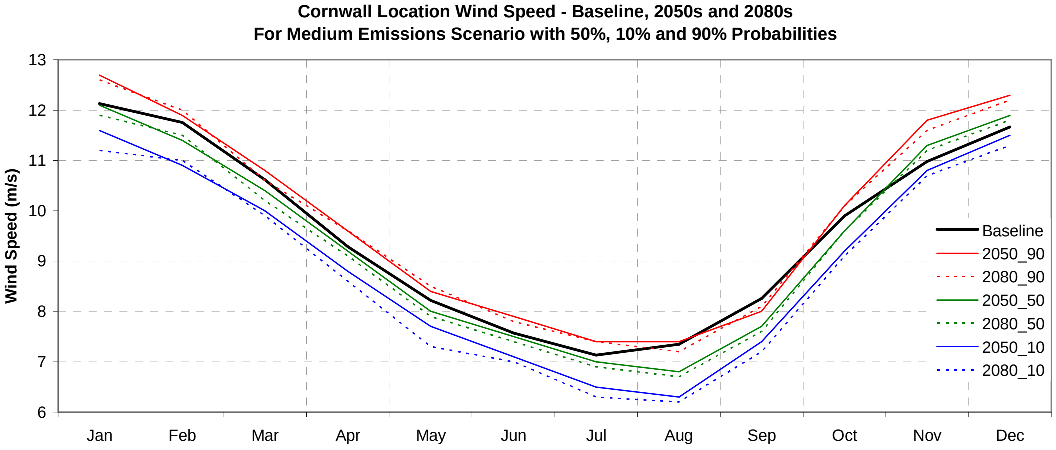


Figure D-6: Cornwall location - Projected Wind Speed change from baseline

Appendix E

	Capacity Factor	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Oykel	**baseline mean + 2 * std dev**	0.92	0.86	0.85	0.66	0.39	0.44	0.45	0.55	0.74	0.88	0.96	0.93
	baseline mean	0.88	0.80	0.79	0.58	0.32	0.35	0.38	0.48	0.66	0.82	0.92	0.89
	baseline mean - 2 * std dev	0.83	0.75	0.73	0.50	0.24	0.26	0.30	0.41	0.58	0.77	0.89	0.85
Oykel	**future mean + 2 * std dev**	0.93	0.87	0.84	0.65	0.37	0.40	0.39	0.44	0.71	0.86	0.96	0.95
	future mean	0.89	0.81	0.78	0.57	0.30	0.31	0.32	0.37	0.63	0.81	0.92	0.91
	future mean - 2 * std dev	0.84	0.76	0.72	0.50	0.22	0.22	0.24	0.30	0.55	0.76	0.89	0.87
	Ewe												
Ewe	**baseline mean + 2 * std dev**	0.92	0.87	0.84	0.65	0.46	0.44	0.48	0.55	0.75	0.90	0.93	0.92
	baseline mean	0.85	0.79	0.76	0.57	0.37	0.35	0.40	0.46	0.66	0.83	0.87	0.87
	baseline mean - 2 * std dev	0.77	0.71	0.68	0.49	0.28	0.26	0.31	0.37	0.58	0.75	0.81	0.82
Ewe	**future mean + 2 * std dev**	0.96	0.92	0.89	0.68	0.47	0.43	0.42	0.46	0.75	0.91	0.97	0.97
	future mean	0.89	0.83	0.80	0.60	0.38	0.34	0.33	0.37	0.66	0.84	0.91	0.91
	future mean - 2 * std dev	0.82	0.75	0.72	0.52	0.29	0.25	0.25	0.28	0.58	0.77	0.85	0.86
	Cree												
Cree	**baseline mean + 2 * std dev**	0.91	0.85	0.81	0.63	0.44	0.44	0.51	0.64	0.78	0.88	0.93	0.91
	baseline mean	0.86	0.79	0.75	0.55	0.37	0.36	0.43	0.56	0.71	0.83	0.90	0.87
	baseline mean - 2 * std dev	0.82	0.74	0.68	0.47	0.30	0.28	0.34	0.48	0.64	0.78	0.87	0.83
Cree	**future mean + 2 * std dev**	0.93	0.88	0.80	0.61	0.42	0.35	0.39	0.46	0.71	0.86	0.95	0.93
	future mean	0.88	0.82	0.74	0.53	0.35	0.27	0.31	0.38	0.64	0.82	0.92	0.89
	future mean - 2 * std dev	0.83	0.77	0.68	0.45	0.28	0.19	0.23	0.30	0.56	0.77	0.89	0.85
	Irvine												
Irvine	**baseline mean + 2 * std dev**	0.97	0.94	0.86	0.68	0.38	0.33	0.42	0.58	0.83	0.95	0.98	0.95
	baseline mean	0.94	0.90	0.80	0.58	0.31	0.25	0.33	0.49	0.76	0.90	0.96	0.92
	baseline mean - 2 * std dev	0.91	0.87	0.74	0.48	0.23	0.16	0.23	0.40	0.69	0.85	0.93	0.88
Irvine	**future mean + 2 * std dev**	0.98	0.94	0.84	0.65	0.35	0.24	0.32	0.39	0.73	0.91	0.98	0.97
	future mean	0.95	0.90	0.78	0.55	0.27	0.15	0.23	0.29	0.66	0.87	0.96	0.93
	future mean - 2 * std dev	0.92	0.86	0.72	0.45	0.20	0.07	0.13	0.20	0.59	0.82	0.93	0.90
	Deveron												
Deveron	**baseline mean + 2 * std dev**	0.98	0.95	0.90	0.74	0.53	0.40	0.37	0.49	0.64	0.84	0.96	0.99
	baseline mean	0.95	0.91	0.83	0.65	0.44	0.31	0.28	0.38	0.53	0.76	0.91	0.96
	baseline mean - 2 * std dev	0.91	0.86	0.77	0.57	0.35	0.22	0.19	0.27	0.42	0.67	0.85	0.92
Deveron	**future mean + 2 * std dev**	0.99	0.97	0.90	0.71	0.50	0.32	0.28	0.36	0.54	0.81	0.97	1.00
	future mean	0.95	0.93	0.84	0.63	0.40	0.23	0.19	0.25	0.43	0.72	0.92	0.96
	future mean + 2 * std dev	0.92	0.88	0.78	0.54	0.31	0.14	0.11	0.15	0.32	0.63	0.86	0.93

Table E-1: Hydro Plant baseline and 2050 medium emissions Capacity Factors (Duncan 2012)

Appendix F

CLIMATE CHANGE AND THE UK SOLAR ENERGY RESOURCE

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Introduction

Solar energy is the most abundant renewable energy source available on Earth. It presently counts for a very small proportion of generated energy, but growing concerns over climate change have helped stimulate a marked growth in implementation over recent years. This is set to dramatically increase as solar technologies mature and costs reduce. However, climate change will affect seasonal cloud cover and impact the available solar resource on the Earth's surface. This study assesses the seasonal solar resource of the UK and investigates the impact climate change could have on the resource. It uses probabilistic regional climate change scenarios released as part of the United Kingdom Climate Projections study (UKCP09).

Data and Methods

A UK solar radiation resource baseline model was developed to represent the present climate. The main data source is 30 years of historical monthly averaged sunshine duration data (Met Office 2009). All sunshine data was first converted to solar radiation using a method described by Suehrcke (2000) then averaged over the 30 year period. Figure 1 shows baseline monthly average radiation resource for summer months (June, July and August).

Validation of the conversion method (Suehrcke 2000) and the baseline model were performed by identifying UK Met Office weather stations measuring both solar radiation and sunshine duration parameters (Met Office 2006), then converting sunshine duration to solar radiation and comparing it to the actual measured solar radiation. Eighteen weather stations were found to meet these requirements and the comparisons were found to be very good. Data for locations on the baseline model where the weather stations are situated also compared well.

The UKCP09 climate change projections provide probabilistic projections for a wide range of climatic variable including 'total downward surface shortwave flux' which is good indicator of solar resource. There are projections for seven 30 year time periods ranging from 2010 to 2099, for three future emission scenarios (low, medium and high) representing alternative climate responses to levels of future emissions, as specified in the Intergovernmental Panel on Climate Change (IPCC) Special Report on Emissions Scenarios (SRES). The probabilistic projections give relative probability of different outcomes and are designed to capture modelling uncertainty. This study will adopt the probabilistic climate change method used by UKCP09 where the central estimate (50% probability) is followed, in brackets, by changes very likely to be exceeded and very likely not to be exceeded at (10 and 90% probability). This study focuses on output for the 2050s. It was generated by projecting the UKCP09 climate change anomalies onto the baseline solar radiation model.

Results

All ranges have been examined and one is presented here. By the 2050s, under a 'medium emissions' scenario, summer months (Figure 1) show solar radiation increases of up to 7.9% (-0.2% to 18.1%) in the south west, these reduce further north with decreases of up to -2.9% (-10.8% to 1.8%) in the north of Scotland. Winter months show a reduction throughout the

UK with extremes of -7.6% (-25.2% to 10.1%) in mid west Scotland. This shows that most parts of southern UK will get sunnier and benefit from increased solar energy resource in summer, while the relatively poor resources in the north will decrease slightly. All regions in winter will have increased cloud cover and slightly reduced solar energy resource. The UK will see an overall annual increase of 2.6% (-1.1% to 6.5%), which is positive news for the viability of solar technologies, particularly in southern regions and would correlate well with increased use of air cooling systems due to the increased temperatures. However, the resource will be more seasonally variable and regional resource differences will be further reinforced.

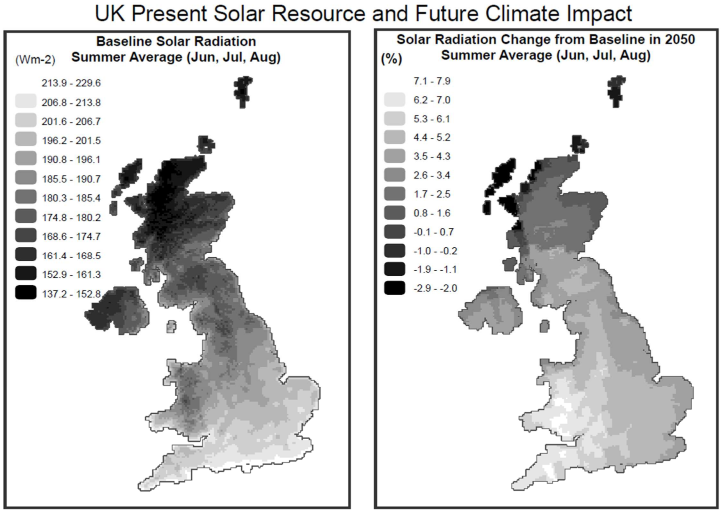

Figure 27. Present UK average solar radiation resource for summer months (jun, jul, aug) and a future climate change projection for the 2050's.

Conclusion

Accurate estimations of mean monthly solar radiation resource have been generated from mean monthly sunshine duration measurement data using a method described by Suehrcke(2000). A baseline model of present climate UK solar radiation has been developed and validated. UKCP09 climate change projections have been used to show climate change impact in percent change relative from baseline.

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References

Suehrcke, H. 2000. On the relationship between duration of sunshine and solar radiation on the earth's surface: Angström's equation revisited. *Solar Energy* **68**, pp. 417–425.

UK Meteorological Office (2009a). UKCP09: Gridded Observation Data Sets. 25 km Gridded Data. Sunshine Duration Hours. Retrieved October 2009, from http://www.metoffice.gov.uk/climatechange/science/monitoring/ukcp09/download/index.html

UK Meteorological Office (2009b). UKCP09: Gridded Wind Speed Data Sets. 25 km Gridded Data. Sunshine Duration Hours. Retrieved October 2009, from http://www.metoffice.gov.uk/climatechange/science/monitoring/ukcp09/download/index.html

UK Meteorological Office (2006). MIDAS Land Surface Stations data (1853-current). British Atmospheric Data Centre. Retrieved October 2009, from http://badc.nerc.ac.uk/data/ukmo-midas

Boehme TA, Wallace R. Hindcasting hourly wind power across Scotland based on met station data. *Wind Energy* 2008; **11**: 233–244.

Harrison, G. P., Cradden, L. C., Chick, J.P. (2008). Preliminary assessment of climate change impacts on the UK onshore wind energy resource, *Energy Sources*, **30** (14), Sept 2008, 1286-1299. **Invited paper** for Special Issue on "Global Climate Change and Sustainable Energy Development". Retrieved October 2011 from: http://www.see.ed.ac.uk/~gph/publications/EnergySourcesDraft.pdf