

Location planning of future offshore wind farms to account for climate change-driven extreme weather events



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Thank you, Allah ...

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Abstract

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The exorbitant electricity generation expense is the primary obstacle to the proliferation of wind energy technology. Industry specialists predicted in 2020 that the cost of offshore and onshore wind energy would diminish by 37-49% by 2050, resulting in a surge of wind farm constructions. The vast amount of available space in marine locations enables the installation of larger offshore wind farms (OWF) with greater capacity. Furthermore, the abundant wind resources in sea areas produce more energy, making it the primary driver behind the expansion of OWFs. Climate change should be considered in the planning stage of future OWF expansion, as it will lead to more frequent and intense extreme weather events (EWE). Generally, wind turbines are built to a particular standard of past or current climate conditions, such that their long service life equals 25 years. As a consequence of climate change, a wind turbine will be exposed more frequently to EWEs than those for which they were designed, which may lead to decreased operating performance and physical damage to the turbine structure. Given this, there is a need to investigate the planning and siting of OWF to ensure resilience to future decrease in wind generation and future increase in weather extremes. This study showcases how OWF spatial planning in the UK exclusive economic zone (EEZ) could become vulnerable to extreme wind events in the future. The research focuses on two critical aspects of EWEs: firstly, the possibility of future changes in extremely HWE that surpass both the wind turbine cut-out wind speed and the 50-year return period extreme loading definition. Secondly, the study examines extreme LWE by analysing intensities for still wind across multiple time windows to predict their occurrence in the future. Additionally, the future changes in wind production and the future stability of wind power have been considered. The UK climate projections (UKCP18) is used in a cutting-edge horizontal resolution of 2.2 km to investigate future climate change projection. Mean wind speed, maximum wind gust, mean temperature, and mean pressure datasets are used to conduct the research. The research output greatly supports planners and stakeholders in designing their future wind energy projects and the design of better risk mitigation policies for future siting of OWF.

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Acronyms

AHP	Analytic Hierarchy Process
CPM	Convection permitting climate model projections
CF	Capacity factor
CDF	Cumulative distribution function
CapEx	Capital expenditures
COV	Coefficient of variation
Cocoso	Combined Compromise Solution
DC	Distance to Coast
EEZ	Exclusive economic zone
EWE	extreme weather events
ECMWF	European Centre for Medium-Range Weather
ERA5	ECMWF Reanalysis version 5
EWPM	Exponentially Weighted Product Model
GIS	Geographic Information System
GEV	Generalised extreme value
HVAC	High voltage alternating current
HVDC	High-voltage direct current
HWE	High wind speed event
IQR	Interquartile ranges
IEC	International Electrotechnical Commission
IPCC	Intergovernmental Panel on Climate Change
K-S	Kolmogorov-Smirnov
LCOE	Levelized Cost of Energy
LWE	Low wind speed event
MAT	Minimum/ Maximum Acceptable Threshold
MW	Megawatts
MCDA	Multi-criteria decision analysis
MSLP	Mean sea level pressure
MAE	Mean Absolute Error
MV	Monthly variation

OWE	Offshore wind energy
OWF	Offshore wind farms
OWT	Offshore wind turbine
O&M	Operations and maintenance
PDF	Probability Density Function
RCP	Representative Concentration Pathway
RC	Relative Change
RR	Risk Ratio
RMSE	Root Mean Square Error
SV	Seasonal variation
SAW	Simple Additive Weighting
TWh	Terawatt-hour
Topsis	Technique for Order Preferences by Similarity to Ideal Solution
UKCP18	UK Climate Projection 2018
WPD	Wind power density
WD	Water Depth
(~)	Approximately
U_{50}	50 year return period
U_{ref}	Reference wind speed

Related Publications

Journal Publication:

- **Abdelaziz et al. 2025a:** S. Abdelaziz, S. N. Sparrow, W. Hua, and D. C. H. Wallom, “Assessing the long-term effects of climate change on offshore wind operations in the UK,” *Energy*, 2025. <https://doi.org/10.1016/j.energy.2025.137062>
- **Abdelaziz et al. 2023b:** S. Abdelaziz, S. N. Sparrow, W. Hua, and D. C. H. Wallom, “Assessing long-term future climate change impacts on extreme low wind events for offshore wind turbines in the UK exclusive economic zone,” *Appl. Energy*, vol. 354, no. PB, p. 122218, 2024, doi: 10.1016/j.apenergy.2023.122218.

Conference Publications:

- **Abdelaziz et al. 2023c:** S. Abdelaziz, S. N. Sparrow, W. Hua, and D. Wallom, “Future Climate Change Impact on Wind Gust for Offshore Wind Turbines Cut-Out Within the UK Exclusive Economic Zone,” in *IEEE Green Technologies Conference*, 2023, vol. 2023-April, pp. 10–14, doi: 10.1109/GreenTech56823.2023.10173830.
- **Abdelaziz et al. 2023d:** S. Abdelaziz, S. N. Sparrow, W. Hua, and D. Wallom, “Extreme Wind Gust Impact on UK Offshore Wind Turbines : Long-Term Return Level Estimation,” 2023, IEEE PES GM 2023. [Online]. Available: https://efaidnbmnnnibpcajpcgclclefindmkaj/https://ora.ox.ac.uk/objects/uuid:543fb86e-37aa-4e70-8718ad5c08a8a512/download_file?file_format=application%2Fpdf&safe_filename=Abdelaziz_et_al_2023_Extreme_wind_gust.pdf&type_of_work=Conference+item.

Poster Publications:

- Sara Abdelaziz, Sarah N. Sparrow, W. Hua, David Wallom, “Resilient Offshore Wind Farm Planning: Integrating Climate Projections and Multi-Criteria Decision Analysis for Optimized Siting in the UK”, ICEM 2025.
- Sara Abdelaziz, Sarah N. Sparrow, W. Hua, David Wallom, “Framework for Offshore wind farms’ future location planning in the UK exclusive economic zone”, EGU2025.
- Sara Abdelaziz, Sarah N. Sparrow, W. Hua, David Wallom, “Evaluating UKCP18 Climate Model Accuracy for Offshore Wind Energy Planning”, IEEE PES GM 2025.
- Sara Abdelaziz, Sarah N. Sparrow, W. Hua, David Wallom, “Offshore wind farms future siting model in the UK exclusive economic zone”, IEEE PES GM 2024.
- Sara Abdelaziz, Sarah N. Sparrow, David Wallom, 2023. Future Climate Change Impact Assessment on Extreme Low Wind Events for Offshore Wind Turbines within the UK Exclusive Economic Zone. 7th International Conference Energy & Meteorology (ICEM 2023), 27th – 29th June 2023, Padove, Italy.

Chapter 1 Introduction

1.1 Motivation

Increasing wind power penetration is crucial to the net zero energy transition [1], [2]. Recently, there has been a notable expansion in the wind energy capacity in Europe, represented by an 18% increase in wind energy installation from 2020 to 2021 [3]. In 2021, the UK has the largest capacity of installed offshore wind farms (OWF) in Europe, with 2.6 GW installed [3]. The same year, wind energy provided 26.1% of UK electricity generation, with offshore wind contributing 14% [4]. Until 2023, the UK's total installed wind capacity onshore and offshore is over 30 GW. Based on the advantages of offshore energy expansion, the UK government's 2030 plan is to expand offshore wind power plants to 33% of the UK's total electricity generation at approximately 30 GW [5]–[7].

The UK government aims for a more sustainable energy model to meet its net-zero target by 2050 [8]. One method proposed to bolster this plan is adding wind energy capacity to the grid and developing new wind farms in offshore locations [9]. Offshore wind energy (OWE) has three crucial advantages: (a) offshore areas generally have a higher average wind speed compared to onshore, which impacts the total annual amount of power produced, (b) marine sites allow larger wind farms to be installed with higher capacity, and (c) the turbulence effect in sea sites is reduced compared to inland sites [10] due to lower frictional drag across the water's surface. Harsh weather conditions in marine environments, the necessary capital expenditure (CapEx), and the impacts on sea life represent the main disadvantages of OWE installations [11].

The large available offshore area leads to a consistent development in offshore wind turbine (OWT) size and power. By growing the size of an OWT, the output capacity for a newly installed OWT will reach 17 MW by 2035, see Figure 1.1 and Table 1.1.

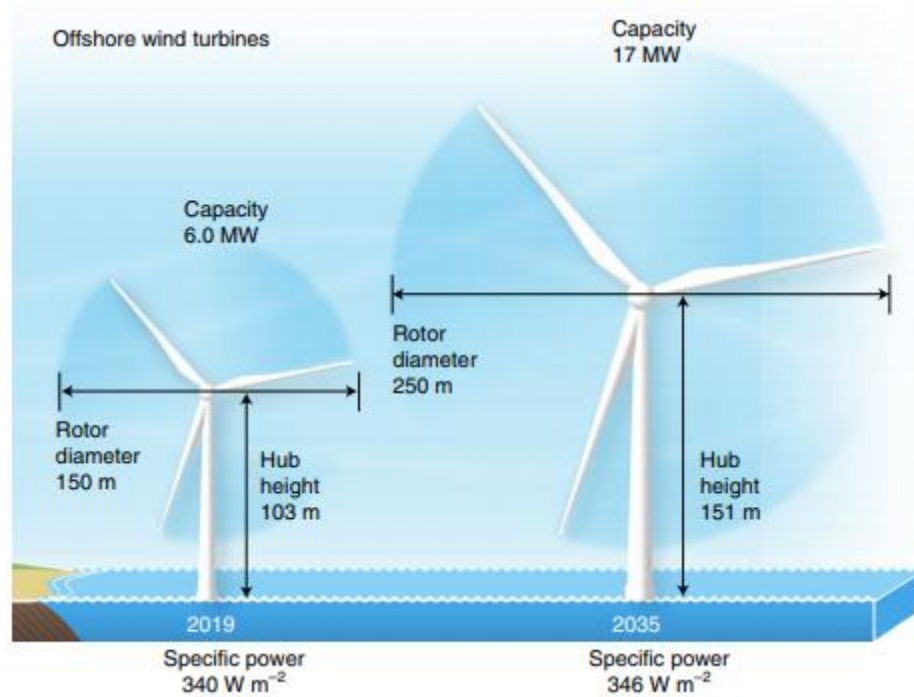


Figure 1.1. Increasing average size and output capacity of offshore wind turbines by 2035 [12].

Table 1.1. Design parameters of a 17 MW future estimated wind turbine [12].

Turbine feature	Values
Hub height	151 m
Rotor diameter	250 m
Capacity	17 MW
Power	346 W/m ²
Type	Offshore wind turbine
Estimated year	2035

The impact of more intense and frequent extreme weather events (EWE) associated with climate change on renewable wind generation poses an increased risk to the wind energy sector itself, as it leads to degraded wind farms performance and additional costs due to physical damage to the turbine structure [13], [14]. Considering these effects when determining siting

locations for OWF would likely lead to installation in locations less prone to EWEs. This can help reduce the need to over-engineer the turbines for deployment, potentially lowering financing costs for specific projects and CapEx due to lower turbine manufacturing costs.

Failure to address climate change adaptation and mitigation could result in severe long-term consequences [15]. The Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report indicated that climate change would likely accelerate, leading to more frequent and stronger EWEs [16]. This would increase the risk of damage to buildings, ecosystems, and humans from these events. On December 12, 2015, an international effort was initiated by the Parties to the United Nations Framework Convention on Climate Change (UNFCCC) [17]. They reached a significant agreement to combat climate change, marking an important milestone. The primary objective of the Paris Agreement is to unite and reinforce the global response to the danger of a warming climate by restricting the rise in global temperature. Due to the growing significance of mitigation strategies, the IPCC requested climate scientists create a new set of scenarios to forecast future climate patterns. These scenarios are represented through representative concentration pathways (RCPs). Each RCP encompasses presumptions about social, physical, and economic changes in our surroundings that will impact climate change [1]. New climate models, such as the UK climate projection (UKCP18) projections, use the RCPs to model future climate scenarios [1]. In this research, the internationally surpassing 2.2 km horizontal resolution model [18] is used to study the impact of extreme wind speed and use temperature and pressure data to study wind production . This climate models uses RCP8.5, which refers to greenhouse gas emissions continuing to grow unmitigated (representing the worst-case climate change scenarios), leading to a global average temperature rise estimation of 4.3°C by 2100 relative to pre-industrial levels [1]. The RCP8.5 is the only available pathway under the 2.2 km resolution in the UKCP18 model; see section 8.2 for more details. According to [19], achieving a reduction of approximately 36% in

wind power variability in the UK is feasible through the strategic distribution of wind power capacity. Moreover, well-considered spatial planning can reduce wind energy costs [16] by developing spatial siting tools that consider all wind turbine production and non-production stages in the context of future atmospheric weather hazards and the associated variability. Selecting the optimal site for the installation of OWF is a complex and essential footstep in the planning stage for OWFs as it is based on various factors, such as environmental parameters, economic, national regulations, and social guidelines [20]. This research focuses on investigating the different regions of the wind turbine power curve, considering the future risk of extreme weather and future variation in wind power generation, and EWEs are defined based on wind turbine manufacturer thresholds. The thresholds represent the operational limit for the wind turbine, such as cut-in speed, cut-off speed, and reference wind speed. Applying these thresholds to future wind period data makes it possible to quantify the effect that likely future wind extremes could have on wind turbine operation in a specific location, thereby informing the optimal siting of future UK OWFs. In addition to atmospheric wind conditions, temperature, and pressure models have been utilised in a future spatial siting model for OWF.

The research also aims to add the economic impact of installing wind farms in locations away from the coastline and the water depth in the established locations. To deal with multiple factors and their interactions to determine the best solution, a multi-criteria decision analysis is employed as this is considered an efficient approach. In MCDA, several factors are engaged to obtain a unified decision as it balances the different criteria to achieve the best solution. Several studies have used MCDA, such as hybrid renewable energy systems and site selection for electrical grids [1]. There are more than 200 MCDA methods; this research aims to use three different MCDA methods (Vikor, Topsis, and COCOSO) to determine the best locations to install future OWF.

Determining the most vulnerable locations to future EWEs will greatly assist the future siting of OWTs. As such, it will support the government's target to achieve net-zero emissions by 2050. It will help avoid exposing wind turbines to future weather extremes, such as lower production emerging from exposing the wind turbine to long periods of low wind speed and from exposing wind turbines to extremely high wind speed. Also, acceleration in wind turbine components caused by high winds can increase the fatigue load on the wind turbine structure. Therefore, all these extreme weather parameters will be integrated with other economic criteria to obtain the most suitable sites to install future OWF in the UK. Also, this research aims to compare our recommendations with preference locations given by the Crown Estate. The Crown estate defines a key resource area for England and Wales offshore locations in the EEZ [21], see Figure 1.2. These areas are defined as a suitable location to site OWF based on physical site drivers, such as quaternary thickness, bedrock lithology, seabed sediments, wind speed, and bathymetry and not capturing criteria such as seabed uses, environmental constraints, etc. [21]. The key resource areas have been classified based on the technology groups linked to the physical site drivers [21].

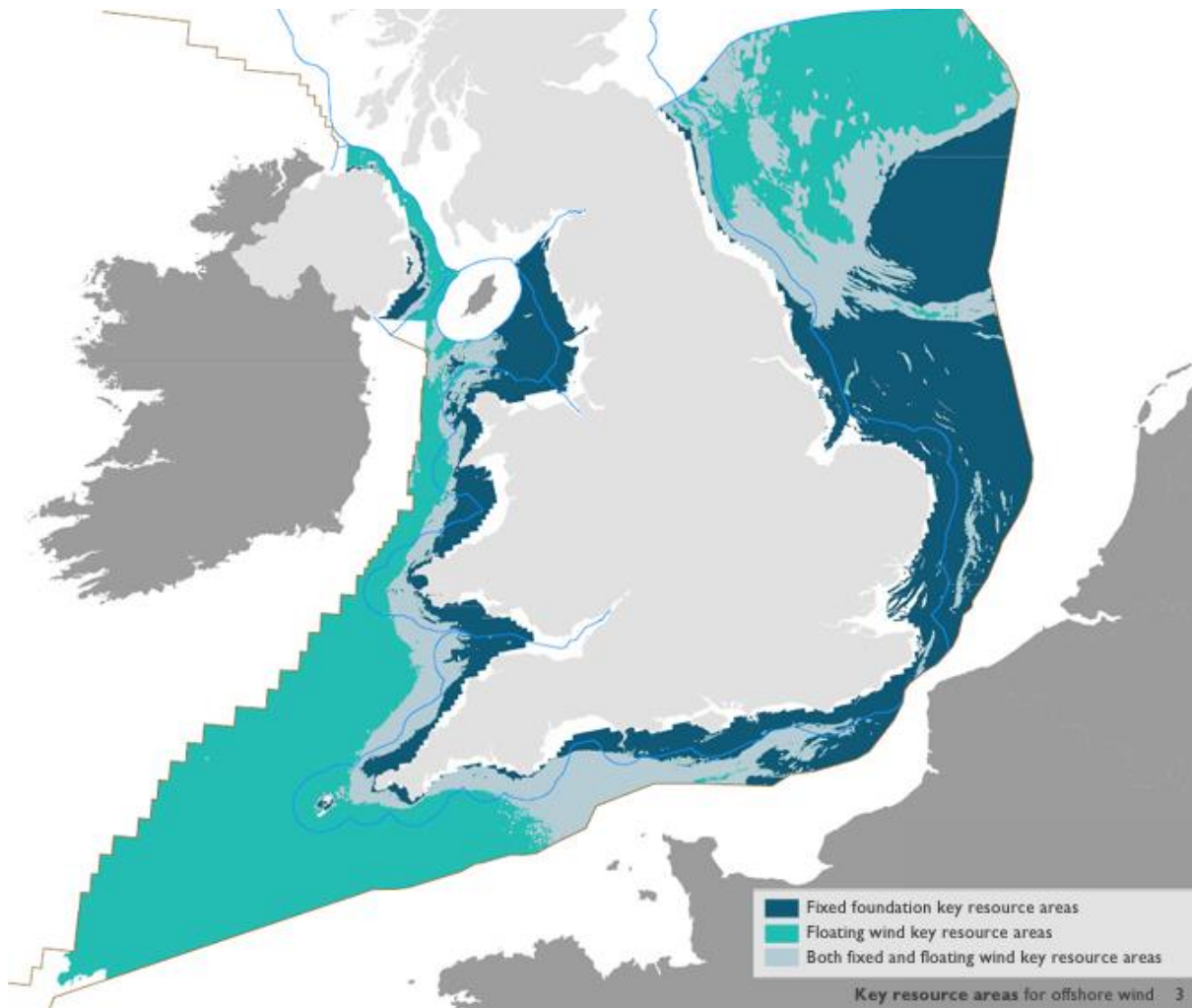


Figure 1.2. Key resource areas identified by the Crown Estate [21].

1.2 Research goals and questions

The goals of this research are:

1. Spatial Investigation of Future Extreme Weather Events (EWEs):
 - Conduct a spatial analysis of future extreme weather events, focusing on extremely high wind speed events (HWEs) and low wind speed events (LWEs).
 - Understand the potential changes in wind power generation and future generation capacity within the UK exclusive economic zone (EEZ).
2. Framework Development for Offshore Wind Farms (OWFs):

- Develop a framework that integrates the investigation of future extreme weather events with the future siting of offshore wind farms.
- Consider economic criteria to identify the most suitable locations for expanding wind energy technology.

Key Research Questions:

1. Impact of Extreme Weather on Offshore Wind Farms:

- How will high wind speed events and low wind speed events affect UK offshore wind farms?

2. Optimal Locations for Future Offshore Wind Farms:

- Among the four central study regions in the UK EEZ, which locations are the best for future offshore wind farms, considering energy production, extreme weather events, and economic criteria?

3. Risk Assessment of Planned Wind Farm Locations:

- Are the currently planned offshore wind farm locations at increased risk from future extreme weather events, and are they suitable for repowering in the future?

Achieving these research goals will provide critical insights into the effects of climate change on offshore wind energy planning, ensuring resilience and sustainability in future wind energy projects.

1.3 Thesis scope

The thesis proposes to identify the best OWF locations based on the wind turbine power curve of four primary wind speed regions. The analysis employs various statistical techniques

specific to each of these four regions. The thesis aims to identify the most desirable future UK EEZ locations for OWF installation by utilising three Multiple Criteria Decision Analysis (MCDA) techniques, incorporating the insights gained from analysing the four wind production regions. The key contribution of this thesis is to shed light on the role of climate change and EWEs in future siting for OWF in the UK EEZ. Prior research in OWF siting has provided valuable perspectives on the evolution and functioning of the OWF siting process, considering current or past weather data and financial, economic, and geographical factors. However, climate change models as a key factor in the future change in wind power generation have received surprisingly little attention from OWF stakeholders and planners. By investigating two future periods and examining seasonal and monthly wind power stability, capacity factor (CF), and extreme high and LWE on future climate change, this section showcases the thesis content and provides novel insights into the impacts of climate change on the future siting of OWF.

1.4 Thesis organisation

The thesis consists of eight chapters, with chapter 1 introducing the research topic. It outlines the overarching motivation and goals, and the research questions. Chapter 2 provides a brief background for the research and a summary of the main work done in the thesis. The chapter describes the gap in the literature and the thesis contribution, leading to the novel approach and analysis concepts developed to focus on future wind energy production, extreme HWEs, and extremely LWEs, respectively. Also, it covers the literature concerning the broad aim of the thesis: using the climate model as a key factor to site future OWFs. Chapter 3 provides the necessary explanation for the data used in this research, including the climate model verification and the adopted regions in the UK EEZ. Chapter 4 uses mean wind speed data in historical and two future periods to investigate future changes in multiple factors that affect wind power generation. Chapter 5 and chapter 6 analyse the possible future extreme

LWE and HWE, respectively. Chapter 7 gather all the results from chapter 4, 5, and 6 into one model using three MCDA methods to provide recommendations of the best locations in the UK EEZ to site OWF. Chapter 8 provides the conclusions drawn from the study and discusses the research future directions. The thesis comprehensively analyses various aspects of wind energy production and offers new insights and approaches for improving OWF future siting. The analysis in this research uses Python and ArcMap and the University of Oxford Advanced Research Computing (ARC)¹ to facilitate the study of the extensive large amount of weather data that covers the UK EEZ in 2.2 km horizontal resolution.

¹ <http://dx.doi.org/10.5281/zenodo.22558>

Chapter 2 Background and links to thesis contribution

This work is conducted in two fields: wind renewable energy and future extreme weather events (EWEs). The research will focus on integrating both fields in the context of future planning of OWF's. As such, the background introduced here will highlight the necessary knowledge for wind turbine power curve regions and the concept of EWEs and link it to the thesis's main contribution.

2.1 The effects of climate change and extreme weather events on wind turbines.

Climate change and extreme weather are a matter of growing interest due to the risk posed to society. The growing impacts on the worldwide infrastructure, communities, and ecosystems of recent extreme events have driven this concern. Evidence also shows that climate change has led to more intense and frequent changes in some types of extreme events [22]. Estimating extreme wind speeds is a key component of wind turbine design for capital costs, structural integrity, and wind turbine selection for a given site [13]. To investigate EWEs and integrate their results in the decision of the siting of OWF, the distribution for the climate model variable is first needed for baseline and future periods. The distributions show the most likely (mean) and range (variability) of the climate model for a given period. By comparing distributions for different climate periods, the future change in extreme event occurrence represented in the tail of the distribution can be highlighted. For example, in Figure 2.1, the solid lines represent the hypothetical probability density function (PDF) for the temperature distribution under current climate conditions. The dotted line in each panel shows how different future climate scenarios could alter this distribution, thereby changing

the likelihood of both hot and cold temperature extremes. Events occurring in a mid-range temperature (events that fall near the centre) are more likely to occur, and events that occur in upper and lower extremes temperature (events that fall near the tail) have a smaller probability of occurring [23]. Figure 2.1 (a) shows a shift of the entire distribution toward a warmer climate, which could lead to more extreme hot weather events and fewer extreme cold weather events. Figure 2.1 (b) shows that an increased variability without a shift could lead to a lower probability of mid-range events and more extreme heat and cold events. Figure 2.1 (c) shows that the asymmetric shape of the distribution could result in no change in the mean but more change toward extreme hot weather. In general, an asymmetric shape can lead to differing the probability of occurrence of extreme events on both ends of the distribution [22], [23].

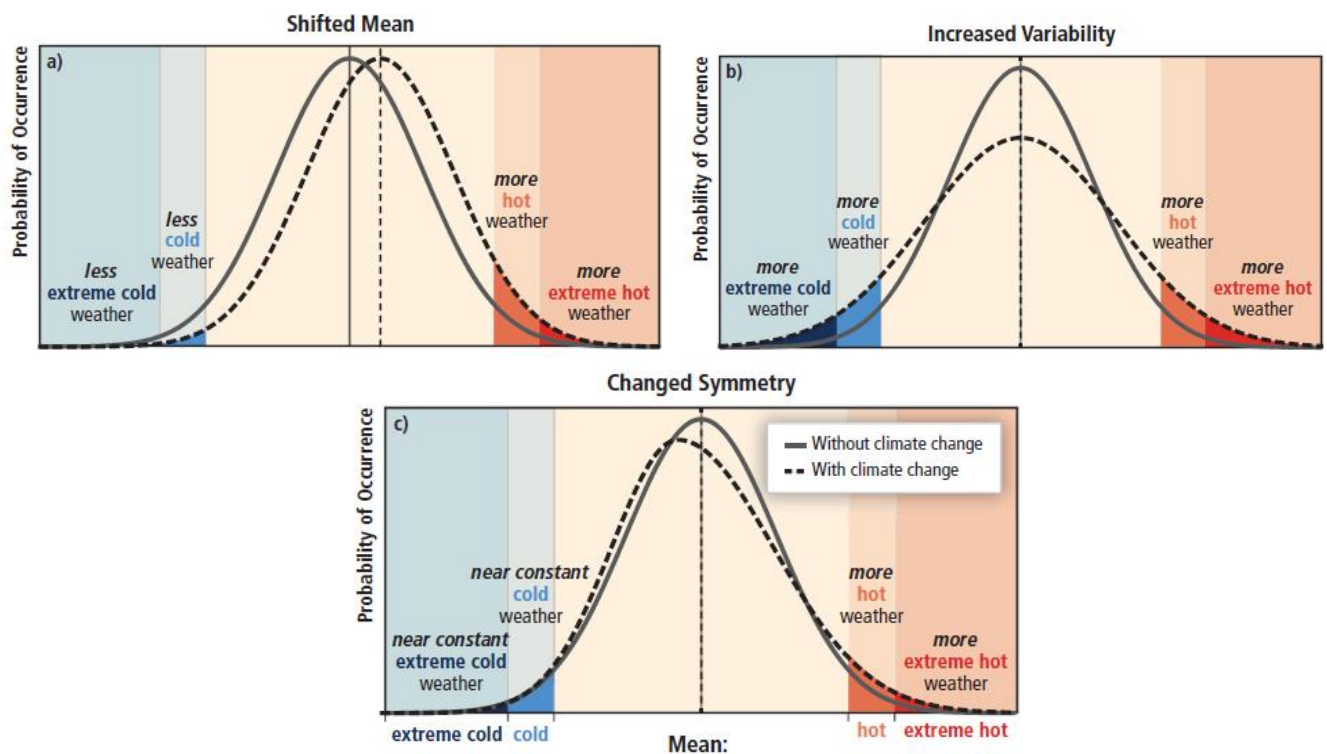


Figure 2.1. Conceptual representation of the world with and without climate change showing different distribution. (a) a shift of the entire distribution toward a warmer climate (b) increased variability without a distribution shift (c) Asymmetric distribution shape [22], [23].

The EWE needs to be defined in the context of the OWF application. According to the World Meteorological Organisation [24], defining an EWE must be in one of the following

contexts: 1- It exceeds a threshold with a certain impact. 2- It is extreme due to its rarity. This can be based on return period or a percentile-based threshold, as in the event variable's upper 90th, 95th, and 99th percentile. This research uses the first method to define EWEs, as event thresholds directly affect wind turbines operation and generating capacity. As described in the following section, the thresholds are taken from the wind turbine operation and non-operation conditions.

2.2 Wind turbine operation and non-operation conditions

This section discusses the wind turbine operating conditions associated with the wind turbine power curve. Wind potential is essential for siting OWT in the planning stage. It indicates the percentage of electricity produced in different regions, therefore, the economic viability of the investment in different areas [25]. The normal and extreme operating conditions for wind turbine were investigated in this thesis.

Though optimised for a particular windspeed, a wind turbine is designed to generate power over as wide a range of wind speeds as possible. This relationship between wind speed and electrical generation output is described within a power curve [26]. An example power curve is shown in Figure 2.2 with key features and regions labelled. The cut-in value defines this range ($v_{cut\ in}$) or minimum wind speed for generation, and the cut-off value ($v_{cut\ off}$) or maximum wind speed for generation. For wind speed less than $v_{cut\ in}$ the wind turbine does not produce energy (Region 1), chapter 5 uses daily mean wind speed to investigate $v_{cut\ in}$ in context of extreme LWE. For wind speed greater than the $v_{cut\ in}$, energy production increases as the cube of wind speed (Region 2) until the rated wind speed (v_{rated}) is reached, the v_{rated} is the point at which maximum power generation is reached. For wind speeds between the v_{rated} and $v_{cut\ off}$ the power generated is constant (Region 3). Chapter 4 uses hourly and daily

mean wind speed to investigate future wind power generation. If the $v_{cut\ off}$ is exceeded, the wind turbine is shut off to prevent damage due to acceleration to its internal components (Region 4) [26]. The value of $v_{cut\ off}$ differ from one type of wind turbine to another, but the most common value in the literature for $v_{cut\ off}$ is 25 m/s mean wind speed or 35 m/s wind gust. Region 5 represents extreme wind speeds over the 50-year return period (U_{50}) value. Chapter 6 uses hourly maximum wind gust to investigate exceeding 35 m/s cut-out wind gust and U_{50} related to Regions 4 and 5, respectively.

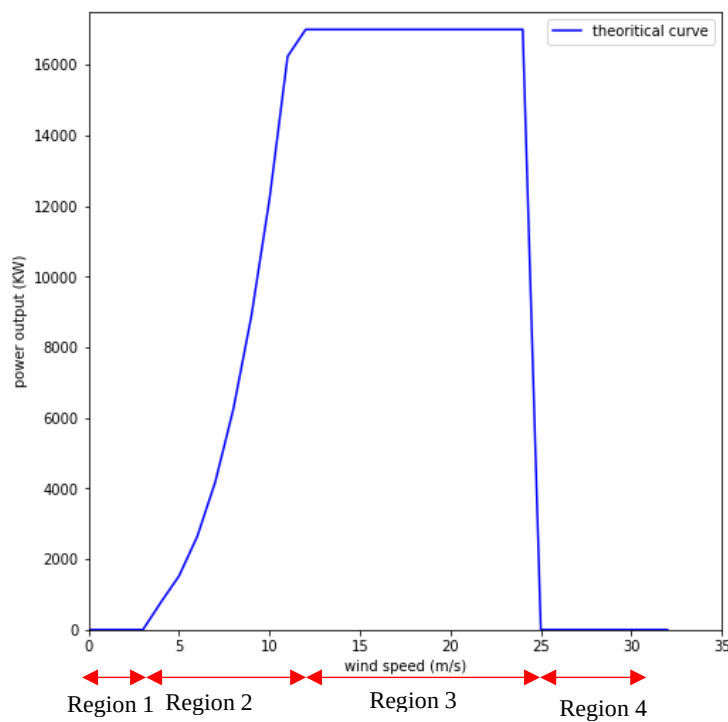


Figure 2.2. Wind turbine power curve.

The different regions of the power curve are represented by the formula in equation (2.1), A is the wind turbine swept area, ρ is the air density [27]:

$$P(x) = \begin{cases} 0, & v < v_{cut\ in} \\ \frac{1}{2} \rho A C_p v^3, & v_{cut\ in} \leq v < v_{rated} \\ p_{rated}, & v_{rated} \leq v < v_{cut\ off} \\ 0, & v \geq v_{cut\ off} \end{cases} \quad (2.1)$$

Where A is the surface area of wind turbine $= \Pi r^2$ (r is the radius $= 125$ m, according to the estimated wind turbine model), C_p is the wind turbine power coefficient $= 0.4058$, v_{rated} is the rated velocity ~ 11.2 m/s (The assumption of rated velocity is made to be in consistency and align with the power coefficient (C_p), this speed is where the turbine is most efficient at converting wind energy into electrical power). The assumed rated velocity is consistent with C_p calculated as the ratio of the actual power extracted by the wind turbine to the theoretical power available in the wind. $v_{cut\ off}$ is the cut-out velocity, $v_{cut\ in}$ is the cut-in velocity, and P_{rated} is the rated power. The wind turbine efficiency is chosen using the Renewableuk estimation for load factor [28], which is based on a rolling average of the past five years using data (on an Unchanged Configuration Basis) from the Digest of UK Energy Statistics published by the DESNZ, using stats 2018-2022 (released in July 2023). Which estimates the offshore wind load factor to be 40.58%. The rated speed of a wind turbine is the wind speed at which it generates its maximum designed power output.

2.3 Literature considering future extreme weather and climate change in the offshore wind farms planning stage

Most studies on climate change's impact on wind energy consider the integration between future climate change models that use the IPCC recommended RCP future warming scenarios to understand the projection on operating and investment values [29], [30]. For example, Hdidouan and Staffell [30] worked on a framework to assess the impact of climate change on the cost of wind energy in the UK. The study used the Earth System Model 2 (ESM2G) future

climate model under RCP 2.6, 6.0, and 8.5. Each future projection covers 95 years (2006-2100) of three hours wind speed. The wind data calculates the energy output and LCOE from wind farms. As a result, different high and low values were found for the CF and a slight increase in the year-to-year variation. However, few studies considered coupling the future climate change and EWE occurrence and severity with the future planning of wind energy from a spatial perspective. Next, the literature that concerns EWEs in the spatial planning phase of OWEs is introduced.

Schillings et al. [31] developed a Decision Support System (DSS) based on GIS to determine the best locations to install OWE in the North Sea. The DSS method is developed and used within the WINDSPEED project. The Intelligent Energy Europe (IEE) program funded the project and delivered a road map to deploy OWE in the North Sea up to 2030. The target of the WINDSPEED project is to examine the potential for OWE deployment in the UK, Norway, Belgium, Germany, Denmark, and the Netherlands regarding spatial and economic constraints. The DSS used spatial data for the sea area to conduct spatial prioritisation analysis considering existing sea uses. The study targeted the shallow area of the North Sea (<50 m). The author did not provide details of the methodology, stating only the scenarios and criteria used in the siting process [31]. The main essential criteria specified in the study were storm surge, mean and extreme wave height, and wind speed at 90 m hub height, but no consideration for the extreme wind speed condition, either as a low wind speed event (LWE) or high wind speed events (HWE) which are subjected to change in the future under climate change. Also, Cradden et al. [32] developed a tool under the MARINA Platform EU FP7 project to select sites in the European region for combined structure wind-wave energy platforms based on the available energy resources. Four fixed criteria, wind speed, wavelength, distance from shore, and water depth, have been chosen to select the most suitable sites around Europe for combined wind and wave resources. The wind data was used from the SKIRON model developed at the

National Kapo Isthrian University of Athens (NKUA). It is ten years of hourly wind speed at 80 m height. The research relies on a simplified analysis to define extreme events, as the 95th percentile of both wind speed and significant wave height represents it. The study concluded that sites along Europe's Atlantic-facing coasts might be suitable for combined wind-wave energy platforms. However, there is a potential risk of accessing some sites because of extreme weather hazards. The limitation in this study lies in defining the extreme wind and wave hazards, as no consideration is given for wind turbine manufacturer thresholds of 50 year return period. Also, it is recommended to use a minimum of 20 years of wind data in the investigation of extreme wind speed to have a reliable estimation for the extreme wind hazard [13]. Moreover, considering future changes in weather will help to gain a complete picture for the future planning of OWTs.

Mytilinou et al. [33] research has been done on Round 3 wind farm zones in the UK to develop a framework to assist wind turbine planners in selecting the optimum wind farm location. The wind farms Rounds represent the governmental plan to expand the wind resources, and till now, they are in a total of four Rounds. The study used high wind speeds exceeding 25 m/s (cut-off mean wind speed) in the planning. The wind speed data covers forty sites around the British Isles for a combined period from January 1977 to December 1979 and from January 1989 to December 1994. The period does not cover the wind turbine lifetime, and the 50-year return period threshold defined by the manufacturer was not used. In 2019 a study considered micro-scale parameters for wind speed historical data to assign the wind energy resources in New Zealand [34]. The parameters included in the study are wind power density (WPD) greater than 200 W/m^2 , effective wind speed occurrence from 5 to 25 m/s, coefficient of variation (COV), monthly variation (MV) index, extreme wind speed with a 30-year return period, and two cost factors, water depth and distance to the coast. Experts were invited to assign a weight for each parameter using the Delphi method. The average weights

have been taken from all experts for each parameter. Finally, the weights from the Delphi method are combined with the normalised value for all factors to get the expected values for wind turbines most suitable installation area. As a result of this method, seven class of suitability has been developed, and three hypothetical scenarios are used to focus on some of the parameters. Results show that New Zealand has an expected value of wind energy above 0.6, meaning it belongs to an affluent area of wind energy, and some small coastal areas have a low expected value. The research objective is promising, Although the hypothetical assumption for the three scenarios has no good justification. Also, the estimation for extreme wind speed is not updated with the IEC standard of 50-year return period and only a 10 m wind speed has been used rather than a real scale for the wind turbine hub height.

Costoya et al. [35] integrated the future climate change models with OWF planning using the CORDEX wind speed model to examine China's future OWE resource. Their method utilised various factors, including the annual wind speed, frequency of wind speed between cut-in (4 m/s) and cut-out velocity (25 m/s), and rich level occurrence, which quantifies the frequency of WPD higher than 200 W/m^2 . To assess the stability of the wind energy resource, the COV and MV were used, and extreme loading was investigated using 50-year return period. Additionally, water depth and distance from the coast were included in the study. Although the model factors focused on the total energy available in the wind flow (WPD) and its variation in the future, the CF was not included in the model, as the model relied on weighting the mentioned factors from the literature [36]. Including an investigation of exceeding the cut-out wind speed and the cut-in wind speed in the context of EWEs would also provide a more comprehensive overview of the suggested model.

Generally, in the UK, several literatures have investigated the suitability for siting OWF. For example, Sean Loughney et al. [37] used MCDA to determine the most suitable floating OWF locations for the northern coast of Scotland. Varvara M et al. [33] have also assessed

OWF in Round 3 zones in the UK using criteria such as LCOE and wind speed greater than 25 m/s. As a result, a suggestion for a preferred location was Seagreen Alpha, near the Isle of May, followed by Moray Firth Eastern Development Area 1, near Wick. Both locations are north of the UK. Abubakr S. Bahaj et al. [38] used AHP for site selection. They developed a parameter Representative Cost Ratio methodology to facilitate the factor pair comparison in constructing the pairwise comparison matrix. The research applied the new method in the UK as a case study and used wind speed, residential areas proximity, wildlife proximity, network proximity, transport links, and historical site criteria. As a result, seven categories were concluded for all suitability ranges, the highest two ranges indicating the best suitable location for siting OWF was found in the northwest, southeast, and some areas in the west of the UK. Zifeng Li et al. [39] used wind speed, wind energy density, water depth, and distance from shore as criteria to select the best production capacity location in the UK. The sites around the UK coastline have been divided into six different zones, and using the MCDA method, the most recommended area was the northern, northwestern, northeastern, and some parts of western waters.

In summary, the changes in extreme weather events can impact existing turbines as high wind speed can cause significant mechanical stress on the structure of wind turbine, also severe and sudden decrease of wind speed can affect the operational efficiency of wind turbine which may lead to more frequent repair and increase the operational cost. The impact on future siting can be in selecting locations less prone to extreme weather events and design and produce a reinforced wind turbine that can resist extreme weather and enhance the control system to adjust to wind production variability.

2.4 Research Gap and Contribution

It can be seen that there is a gap in the literature regarding the impact of climate change and the associated EWEs, represented by extremely HWE and LWE, on future OWF spatial planning. If resilient, reliable, and cost-effective offshore wind generation is to be achieved in the UK, future changes in EWEs must be considered. Additionally, most current analyses overlook extreme HWEs and, therefore, do not account for extreme LWEs. Using future projection data in this research will add more reliability to estimating the most suitable areas to install OWF that are resilient to future changes in EWE.

Most current siting models use climate models with a resolution and timestep incompatible with wind farms. Our approach uses an hourly and daily UKCP18 climate model, which is the necessary time step to quantify the power production. The hourly and daily wind speed is needed to capture WPD and capacity factor similar to what the wind energy operators consider, which increases the predictability of energy output. Hourly and daily data help identify and characterise short-term variability, which is essential for managing intermittent wind power and provides a broader view of trends and long-term patterns.

The UKCP18 model has a 2.2 km horizontal resolution and is compatible with the scale needed for wind farms' spatial area for installation. This exceptionally high resolution in the three periods ensures obtaining the highest possible, reliable spatial information. High-resolution models similar to observation data are highly desirable for capturing mesoscale events (small-scale meteorological phenomena) [40] and investigating extreme weather events.

For several reasons, hourly and daily wind speed data at a 2.2 km resolution may still mask localised LWE. For example, micro-scale meteorological phenomena, such as wind

shadowing, can occur at scales smaller than 2.2 km. Also, LWE might not be detected with less frequent temporal resolution.

This research uses factors investigating production and non-production scales for wind energy generation. Various levels of risk, from the instability of wind production and lower wind power output to the potential for extreme loading on turbine structures and prolonged periods of LWEs. Specifically, there are ten factors used in this research, eight of which are being analysed in detail with consideration to historical and two future scenarios in Chapters 2 to 6: 1- wind power density, 2- capacity factor, 3- coefficient of variation, 4- monthly variation, 5- seasonal variation, 6- return period of 35m/s cut out wind speed, and 7- 50 year return period threshold, and 8- return period of 4m/s threshold. Two more factors are added in Chapter 7: 9- distance to shore and 10- water depth. A brief definition of these factors can be seen in Table 2.1.

Table 2.1. Factors for siting OWF.

#	Factors	Factor definition
F1	Wind power density (WPD)	The quantitative measure of wind energy available at any location at the turbine hub height. (Section 4.5.1)
F2	Capacity factor (CF)	Average power output divided by maximum power capability. (Section 4.5.2)
F3	Coefficient of variation (COV)	It is a statistical measure that represents the relative variability of seasons. It is calculated as the ratio of the standard deviation to the mean, expressed as a percentage. (Section 4.5.3)
F4	Monthly variation (MV)	Refers to the fluctuations or changes in wind power density values over different months. (Section 4.5.3)
F5	Seasonal variation (SV)	Refers to the fluctuations or changes in wind power density values over different seasons. (Section 4.5.3)
F6	Exceeding cut-of wind speed (35m/s)	The 35m/s wind gust represents the point of production stop (no operation for a wind turbine) (Section 6.4.2)
F7	Extreme high wind gusts (U_{50})	Represents the extreme wind turbine structure load. Defined by wind gust corresponding to 50-year return period. (Section 6.4.1)
F8	Extreme low wind speed event	Extreme low wind speed defined using the likelihood of 4m/s to reoccur in 5 days time window (return period). (Section 5.3.4.1)
F9	Distance to the coast (DC)	The offshore wind farm distance to the coast. (Section 7.3)
F10	Water depth (Bathymetry)	Is the measurement of the depth of water in oceans. (Section 7.3)

(*) is a multiplication, (/) is a division.

It is worth noting that accounting for short-term variability represented in hours to days, medium-term variability represented in days to weeks, and long-term variability

represented in seasonal to decades are essential for the effective design, operation, and economic planning of wind energy infrastructure. By examining data across these timescales, stakeholders can better anticipate and mitigate risks associated with wind power production, ensuring more reliable and sustainable energy generation. Short-term variability influences the value of the electricity generated, and medium-term variability impacts operational planning, and long-term variability can affect the overall performance of wind farms.

The analysis of the future expansion of OWF in the UK exclusive economic zone (EEZ) not only considered all factors mentioned in Table 2.1 but also created a spatial preference map for the ten factors. This was achieved by weighing the importance of the ten factors considered in the analysis using experts' opinions and three MCDA methods to achieve the best preference map. To the author's best knowledge, it is the first time to have in one model these ten factors with extreme high and low wind defined by their return period in two future periods.

Some essential criteria for siting future OWF have not been considered in this research due to the unavailability of its accurate estimations for the 2021-2040 and 2061-2080 periods or because of the unknown status of these constraints at the future period considered in the research. Some of these criteria are binary decisions affecting the availability of a site for wind turbine deployment. Examples of these criteria can be the natural gas storage site and pipeline, carbon capture and storage site, meteorological and oceanographic equipment, minerals mining site and minerals aggregates, wave energy site and cable, tidal stream site, and cable, distance from shipping routes, wrecks, obstructions, and heritage marine. These data can be obtained from multiple resources, such as [41]–[47], but they only reflect the current time. In this research, we focused on weather resources to select the preferred locations for future OWF sites. Further criteria should be considered locally in each proposed location to cover additional government regulations. These criteria can affect the practicality of alternative design options (such as choice of fixed- or floating structures), such as soil type and earthquake loads. Also,

geospatial assessment is essential as it can impact the turbine layouts. An expert should consider these criteria before employing the proposed model in this research. Future work could expand the analysis to consider additional factors that can affect different aspects of revenue or costs, such as financial factors and socio-economic impacts, and link the future siting to expected demand.

The detailed thesis contribution and the link to the four publications attached to this report (**Abdelaziz et al. 2025a**, **Abdelaziz et al. 2023b**, **Abdelaziz et al. 2023c**, and **Abdelaziz et al. 2023d**) are summarised as follows:

In chapter 4, the analysis aims to investigate potential future changes in wind power generation. Multiple factors were considered, including WPD, COV, seasonal variation (SV), MV, and CF, to achieve this goal. By examining these factors, a better understanding of the future change in wind energy is provided. Furthermore, the concept of the minimum/ Maximum acceptable threshold (MAT) is introduced, a reference point for determining the most suitable regions within the UK EEZ to install OWF. The MAT determines the EEZ regions that meet the necessary criteria for wind energy production and, therefore, are most suitable for the siting of future OWF projects. The analysis has been submitted to the Elsevier Cleaner Production Journal (**Abdelaziz et al. 2025a**).

Chapter 5 introduces an analysis of extreme LWEs, exploring various approaches to understand better how wind speeds' duration and intensity below a specific cut-in wind speed threshold may change in two future periods. Specifically, analysing consecutive days' duration with LWEs under certain cut-in thresholds. Additionally, the return period for wind speeds of 4 m/s, 5 m/s, and 6 m/s is calculated using a five-day running mean. An in-depth investigation of the 4 m/s threshold using six, seven, and eight-day running means was investigated in depth. Through these analyses, the aim is to understand how extremely LWEs may change in the future, which can inform decisions about OWF siting and design. The results of this chapter

have been accepted as an abstract in the International Conference Energy & Meteorology (ICEM) 2023 and in Elsevier Journal of Applied Energy (**Abdelaziz et al. 2023b**).

Chapter 6 utilise the hourly maximum wind gust dataset to investigate the high values of a wind gust, focusing on two main aspects. Firstly, the cut-out wind gust corresponding to the non-production region in the wind turbine power curve was investigated. Investigating this aspect led to understand better the future occurrence of cut-out wind gusts, leading to wind turbines future shutdown. Secondly, the extreme load threshold defined by a 50-year return period (U_{50}) was investigated. This threshold corresponds to the wind turbine structure's failure risk under extreme wind gust loading. Through this analysis, identifying areas where wind turbines have the highest risk of failure due to extreme wind gust loading is achieved. This can inform decisions about the future wind farm, siting, design, and operation. The analysis of this chapter has been accepted in two conferences, the IEEE Green Tech 2023 for the cut-out wind speed investigation (**Abdelaziz et al. 2023c**) and IEEE Power and energy society general meeting (PES GM) 2023 for U_{50} investigation (**Abdelaziz et al. 2023d**).

In chapter 7, the leading eight factors extracted from chapters 4 to 6 and two economic factors will be considered for each climate period to set the preferred locations for siting OWF. Experts opinions have been used to determine the factors weights. Three MCDA methods were utilised to compare their correlated preference locations. As a result, for each of the three chosen MCDA methods, a recommendation for locations where wind speed has the best potential to produce power, simultaneously, more resilient to possible future extreme wind speed and contribute with lower cost for OWF installation was provided.

Chapter 3 Data preparation

This chapter provides an overview of all data preparation necessary for this research, including the use of UKCP18 components, defining regions within the EEZ, and the wind turbine model.

3.1 UKCP18 Future climate model

The UKCP is a government-funded project that forms part of the UK Met Office Hadley Centre Climate Programme. Both the Department for Environment, Food and Rural Affairs (Defra) and the Department of Business, Energy and Industrial Strategy (BEIS) support the UKCP [18]. 20-years ago, the first climate projection model was established as a part of the UK Climate Impacts Programme (UKCIP). The current version, UKCP18 [18], is considered the fourth set of UK climate projection models. It assesses future climate change in the UK [18]. It is an up-to-date climate science made to deliver data for marine and land climate scenarios out to 2100. In this research, the UKCP18 2.2 km local projections for mean temperature, mean pressure, hourly maximum wind gust, and hourly/ daily mean surface wind speed will be used.

This study utilises mean surface wind speed data obtained from convection-permitting climate model projections (CPM) generated as part of the UKCP18 project [1]. The provided data encompasses climate changes for the UK until 2080, downscaled to a horizontal resolution of 2.2 km [48]. The UKCP18 model simulations comprise 12 ensemble members, each representing climate variability within a changing climate context. Starting from March 2023, the UKCP18 generated climate data from 1981 to 2080. In this research, the UKCP18 dataset used encompasses three distinct time periods: the baseline period (1981-2000), representing

historical climate conditions, and two future periods representing the near future (2021-2040) and the far future (2061-2080). Both future periods align with the RCP8.5 scenario, characterised by an estimated global average temperature increase of 4.3°C by 2100 compared to pre-industrial levels [1]. Currently, the 2.2 km UKCP18 UK grid only provides the RCP8.5 pathway.

3.2 UKCP18 ensemble members vs. ERA5

The UKCP18 CPM is a recently established model that primarily focuses on the analysis of land area [1], [49]–[51]. In this study, we seek to compare the 12-ensembles of the UKCP18 model's daily mean wind speed that covers the UK EEZ against the ERA5 (European Centre for Medium-Range Weather (ECMWF) Reanalysis version 5) reanalysis model [7]. The UKCP18 realisation from a set of 12 convection-permitting models (HadREM3-RA11M) driven by perturbed variants of the Met Office Unified Model Global Atmosphere GA7 model (HadREM3-GA705) at 12 km resolution.

The ERA5 reanalysis combines observations from various sources worldwide with model data to generate a dataset that exhibits global consistency. It has been extensively utilised in wind energy assessment studies [52]–[54] and serves as a benchmark for validating model projections [35]. The aim is to identify the UKCP18 ensemble, or the ensemble mean/median, demonstrating the closest statistical resemblance to the ERA5 reanalysis from 1981-2000. The UKCP18 ensembles have been remapped to a spatial resolution of $0.25^\circ \times 0.25^\circ$, similar to the ERA5 resolution, to facilitate a meaningful comparison between the two datasets.

Four different statistics have been used to verify the 12 ensembles. The objective is to evaluate the ability of each ensemble in the local climate model to replicate wind patterns:

- 1- The overlap percentage (OP) analysis, previously employed for validating offshore wind speed projections [55]–[58], is adopted in this investigation. The OP analysis spatially

compares the extent of overlap between the probability density function (PDF) derived from the ERA5 dataset and that obtained from the UKCP18 dataset within the UK EEZ, focusing on the historical period spanning from 1981 to 2000. The OP calculation is as follows:

$$OP = \sum_1^n \text{minimum}(h_m, h_0) * 100 \quad (3.1)$$

Where OP is the overlap percentage, n is equal to 26 and represents the number of bins used to calculate pdf; h_m and h_0 are the UKCP18 and ERA5 frequency values, respectively. When the OP is equal to 100%, it indicates that the corresponding UKCP18 ensemble has effectively replicated the local wind speed projections. Figure 3.1 shows the OP for all EEZ locations. The OP represents the degree of overlap and exhibits an average value of 86.6% across the 12 ensembles for the locations with OP <90%. The ensemble's mean and median are 83.4% and 82.1%, respectively, for the same locations. Ensembles 01, 05, 07, 09, 13, and 15 have the highest average, equal to ~88% for the same locations.

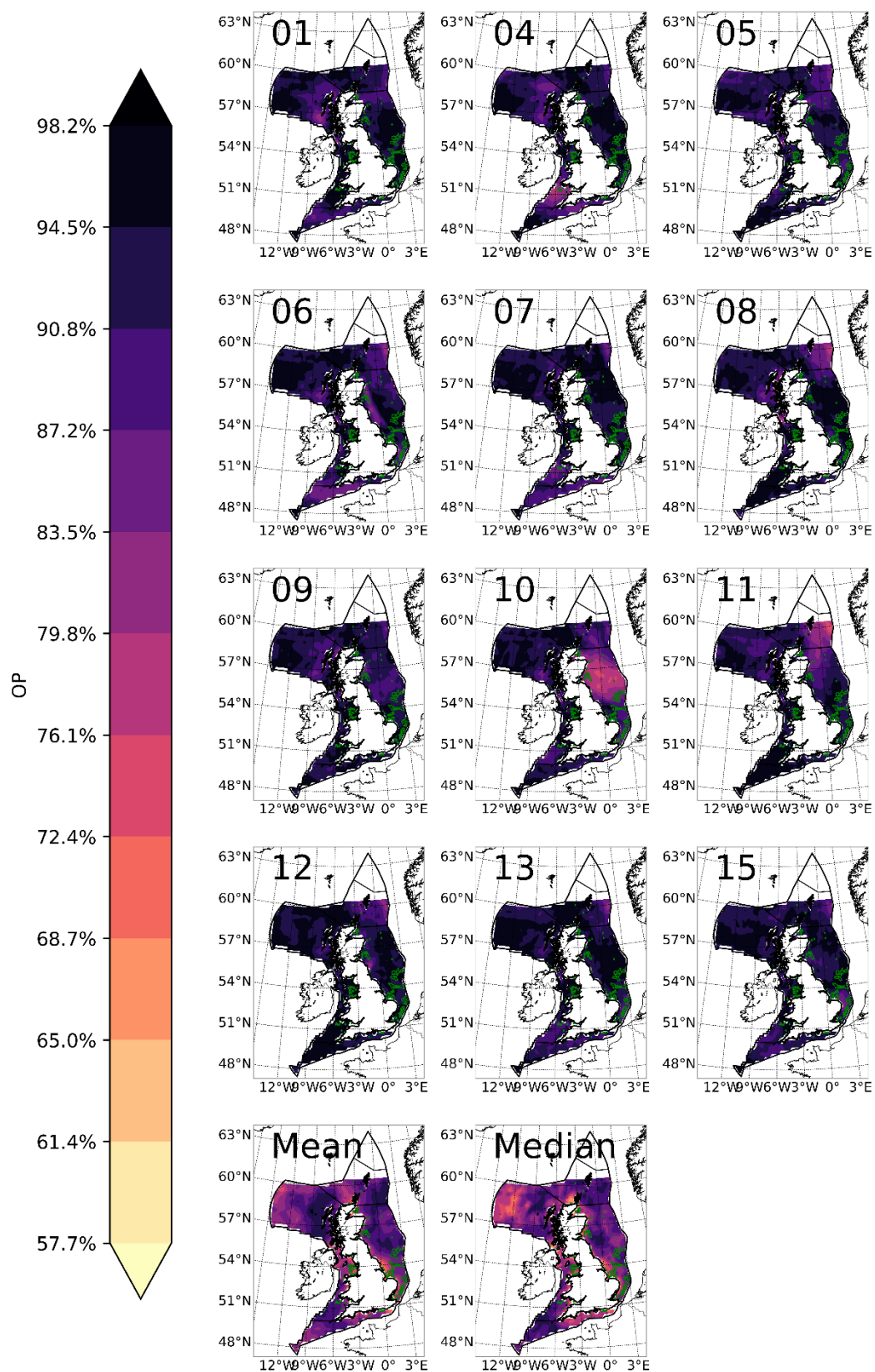


Figure 3.1. The OP using daily mean wind speed are calculated for the 12 ensembles and the ensembles mean/ median for the period 1981-2000.

In Figure 3.2, the MAE for the OP is calculated for all EEZ locations, the average MAE for the 12 ensembles is 0.0055, while 0.0114 and 0.0127 are the MAE for the ensemble mean and median, respectively. The analysis reveals that the ensemble mean and median display relatively less desirable values for OP and MAE. Conversely, for the baseline period of 1981-2000, ensembles 01, 05, 07, 09, 13, and 15 have the highest OP for the less desired locations that have OP <90% and the lowest MAE values for the same locations.

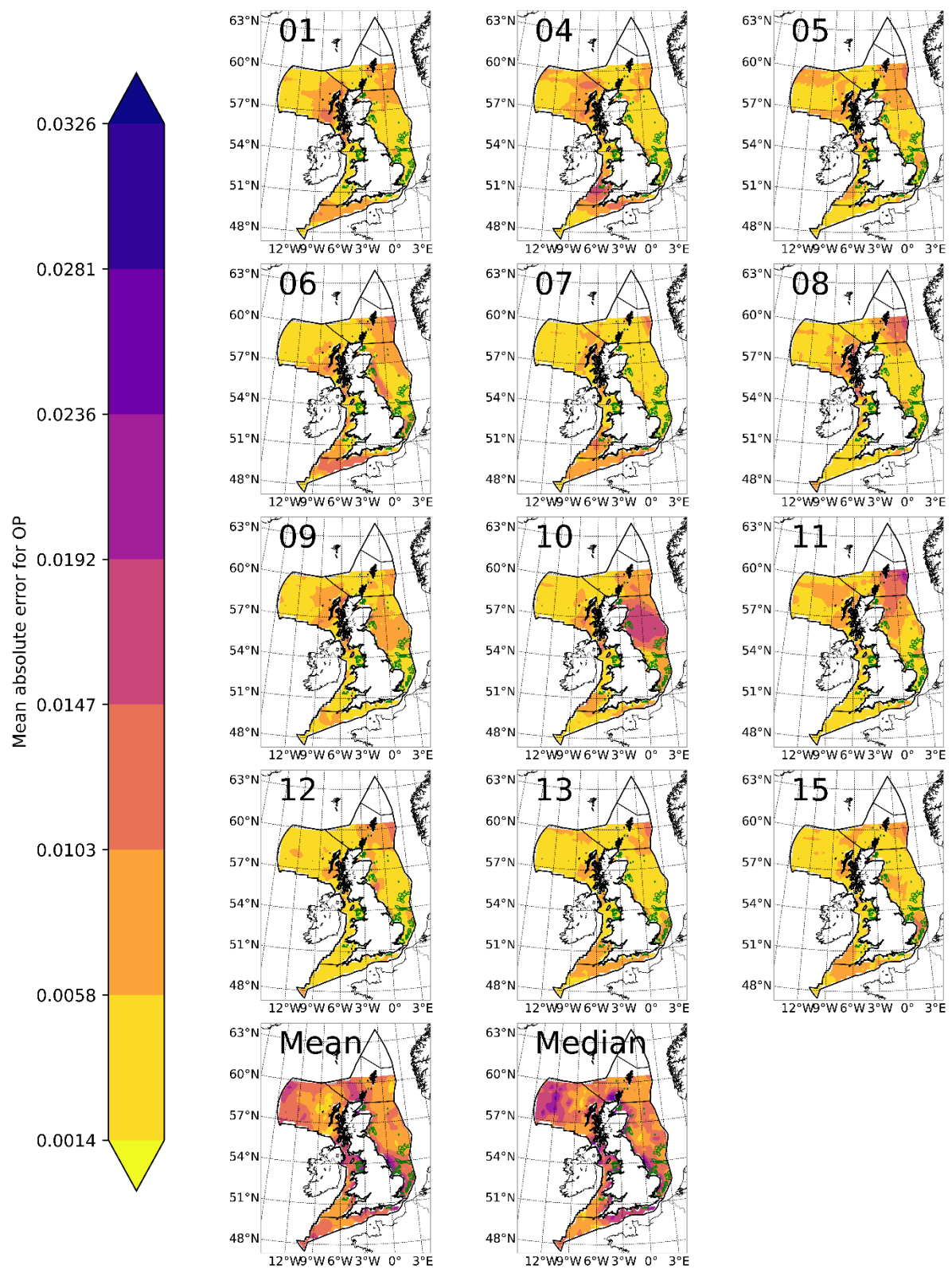


Figure 3.2. The mean absolute error of OP using daily mean wind speed are calculated for the 12 ensembles and the ensembles mean/ median for the period 1981-2000.

2- The spatial variation is quantified in Figure 3.3 for each location in the UK EEZ. For most of the locations, ensembles 01 to 15 have the lowest variation range, equal to 0.003 to 0.6, and ensemble mean/ median has a higher variation range, up to 2.12. Ensembles 07, 08, 12, 13 and 15 have the highest variation as of the mean of all EEZ locations, equal to ~ 0.3 , while ensemble 04 has the lowest variation, equal to ~ 0.2 .

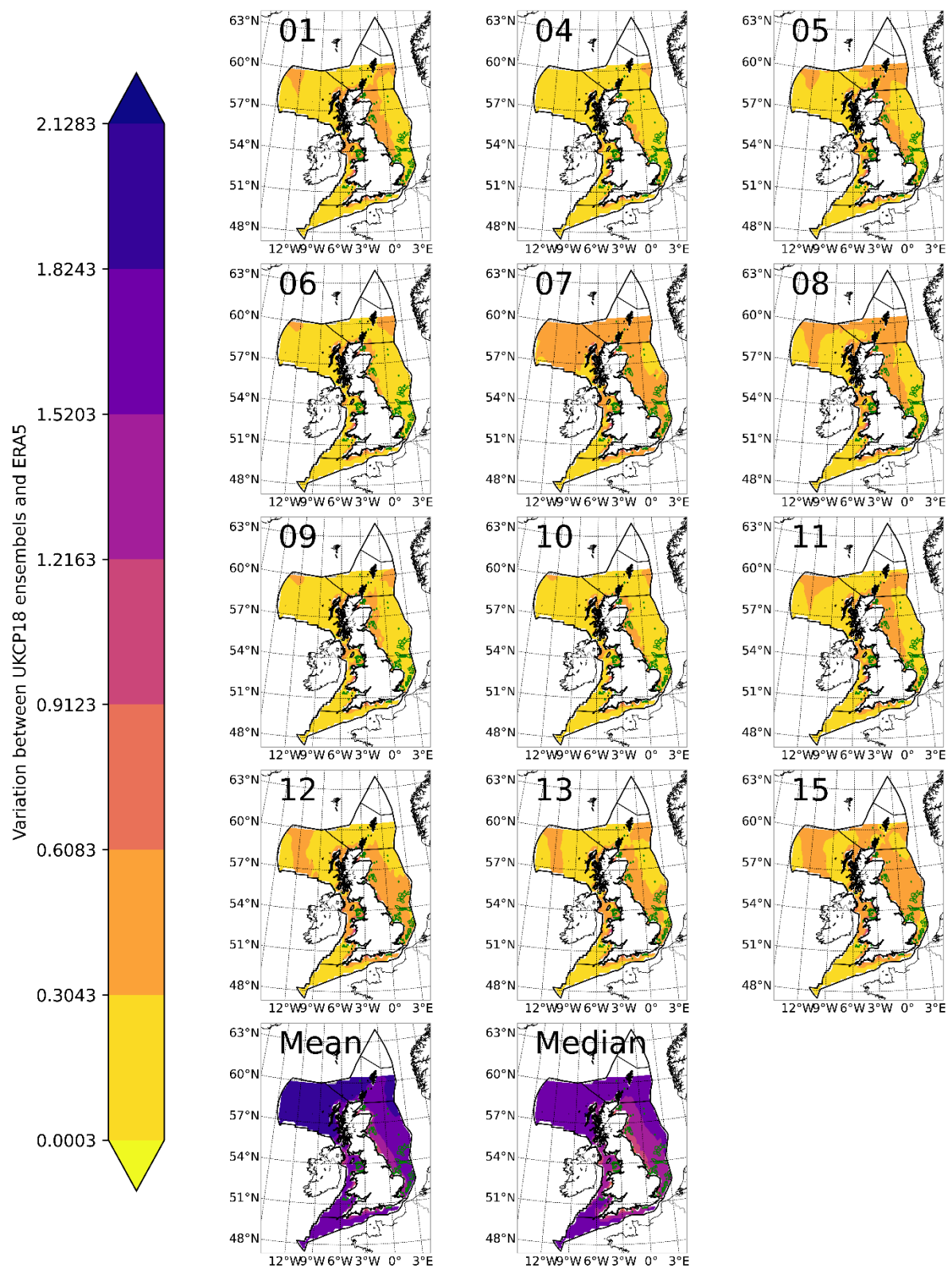


Figure 3.3. The variation of the daily mean wind speed is calculated for the 12 ensembles and the ensemble's mean/ median for the period 1981-2000.

3- The inter-annual variability is compared between the 12 ensemble members and the mean/ median of the ensembles against the ERA5 data to get the best match. In Figure 3.4, the annual mean of the daily mean wind speed for each of the 20 years has been calculated and represented in a line plot. Two different matrices, MAE and RMSE, have been used to detect the bias between the two datasets statistically.

- ❖ The MAE used to compare ERA5 against all ensembles and ensemble mean/ median is approximately 0.4 - 0.8. Ensembles 07 and 12 have the lowest MAE, equal to ~ 0.4 and 0.5 , respectively, and the next lowest MAE values in ensembles 01, 08, 13, and 15, equal to ~ 0.6 . The RMSE is in a range approximately equal to $\sim 0.5 - 0.9$.
- ❖ The maximum differences between the maximum and minimum values for the 12 ensemble are ~ 1.3 m/s.

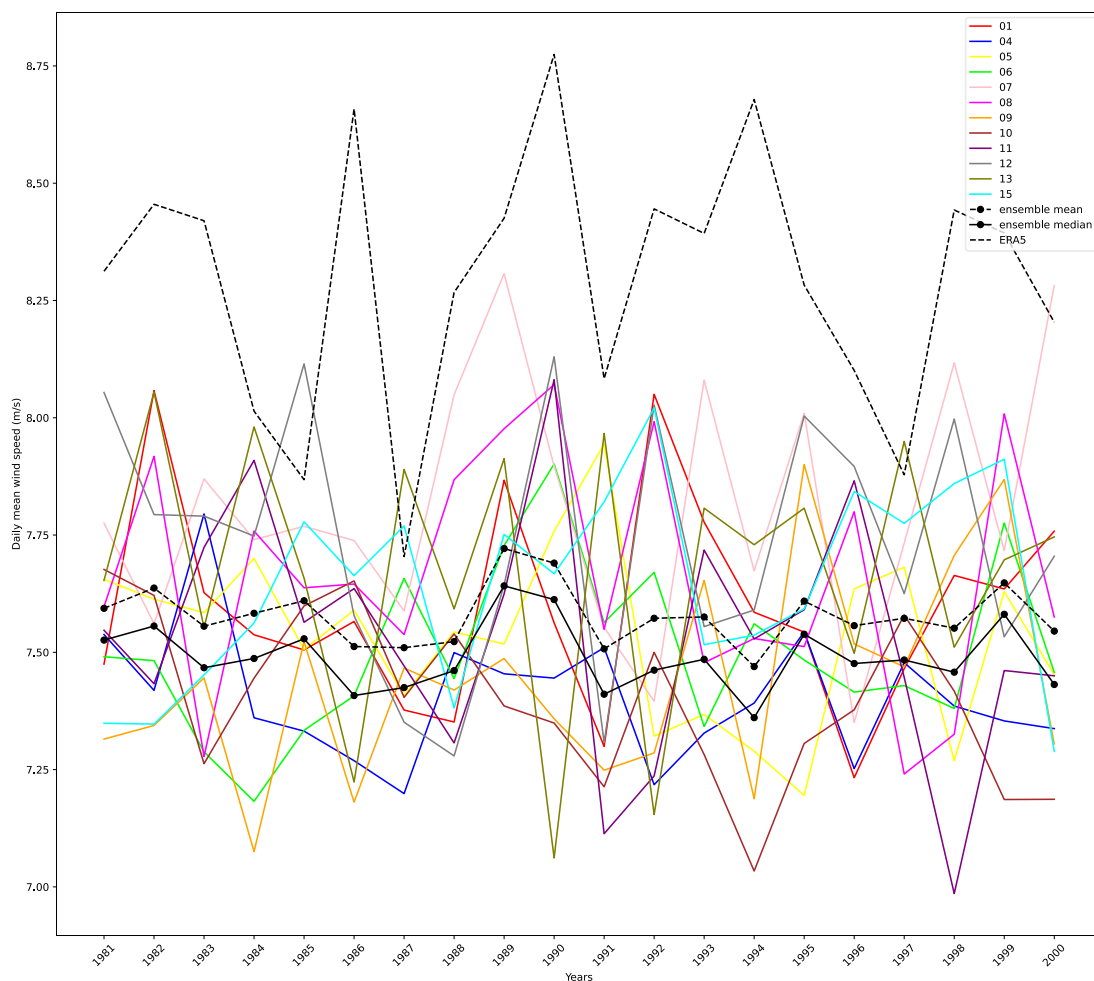


Figure 3.4. Line plot for the yearly mean using daily mean wind speed. The 20 years representing the historical scenario (1981-2000).

4- In order to verify the UKCP18 climate model against ERA5, the following analysis aims to decide whether both models are from a common distribution. In Figure 3.5, the Q-Q-plot for the 12 ensemble members, mean/ median of the ensembles against the ERA5 data, is used to compare the populations of all ensembles against the ERA5. First, a 1:1 gradient reference line is plotted. Ideally, if both data sets come from the same population distribution, the points should fall close to this line. However, if there is a significant departure from this line, then it suggests that the two datasets do not closely follow the same distribution. It is concluded that:

- ❖ The mean/median ensemble and ERA5 models do not appear to have come from populations with a common distribution.
- ❖ The ERA5 values are significantly higher than the corresponding mean/ median ensemble values.
- ❖ The differences increase from mean/ median ensemble in values ≥ 6 m/s.
- ❖ The 12 ensembles have an RMSE ranging from 2.81 to 2.89. Ensembles 10 and 01 have the lowest RMSE, equal to 2.815 and 2.822, respectively. The mean/ median plots have approximately a RMSE value equal to 2.2. Moreover, a light right tail can be seen in the 12 ensembles.

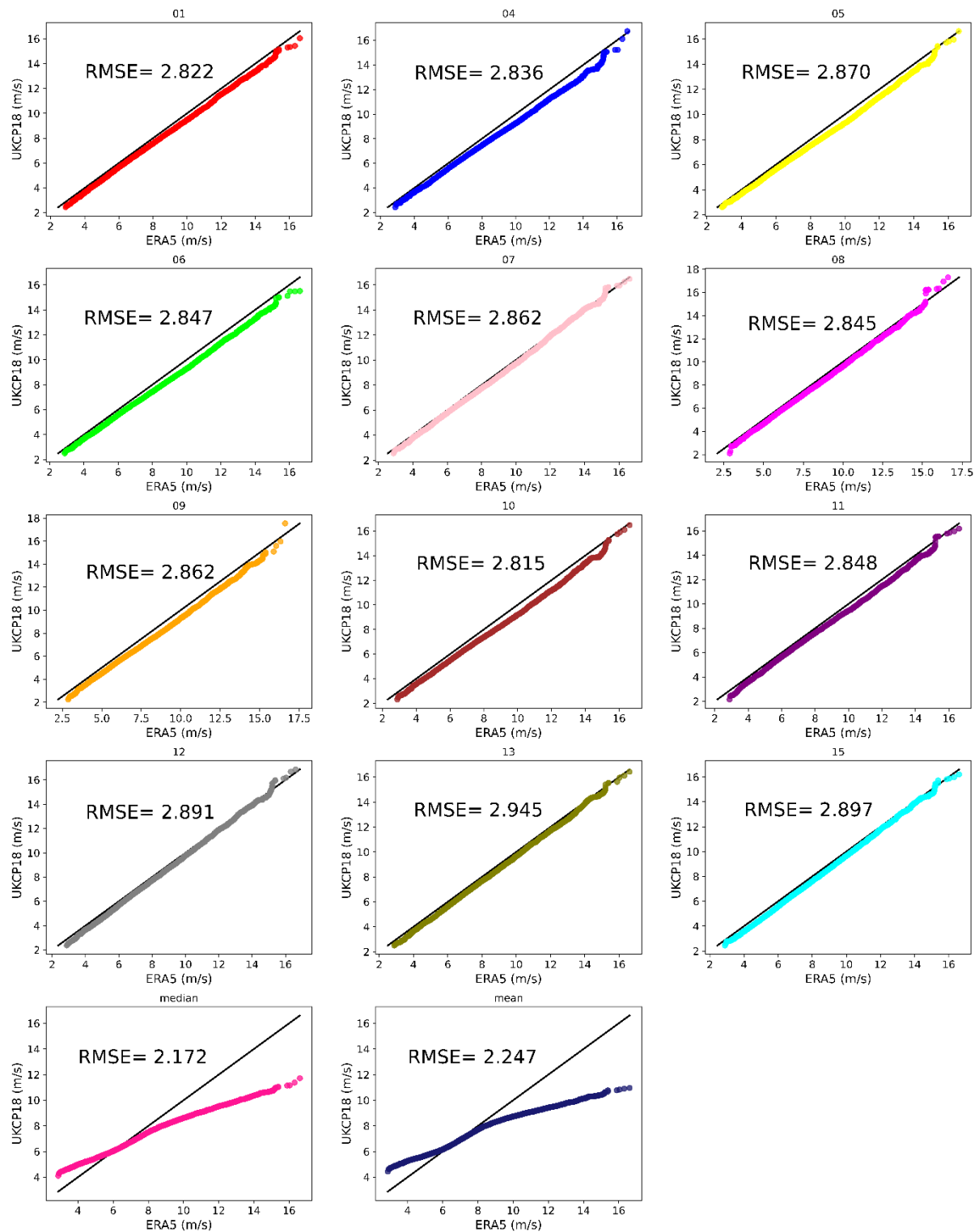


Figure 3.5. Q-Q plot for ERA5 and UKCP18 (12-ensembles/ ensemble mean/ ensemble median) using weighted daily mean wind speed at 10-meter height.

We rely on the high accuracy of the UKCP18 2.2 km high resolution, as according to [59], the improved higher resolution simulations are expected to reduce the uncertainty in climate models. It is beyond the scope of this research to provide a comprehensive discussion of the differences in initial conditions and model physics between the 12 ensembles.

Different analyses showed different ensembles in agreement with ERA5. For example, the OP calculation showed ensembles 01, 05, 07, 09, 13, and 15 to have the best agreement. Variation analysis shows ensemble 04 to have the best agreement with ERA5. On the other hand, the best two ensembles according to the yearly variation analysis are 07 and 12. According to the QQ-plot, the RMSE indicates the best agreement is in ensembles 10 and 01.

The present research utilised ensemble 01, as it is considered the ‘default’ ensemble widely used in the literature as a reference for the UKCP18 model [60]–[63]. There was an attempt to rerun the model on the other eleven ensembles, but because of the computation expensive for the 2.2 km dataset [51], [64] and storage constraints, as the storage needed is approximately 20 TB for the three scenarios in all required datasets (daily mean wind speed, daily mean temperature, daily mean pressure, hourly mean wind speed, hourly maximum wind gust) in addition to the high post-processing storage needed.

In conclusion, using any individual ensemble will be accompanied by uncertainty for its parameters, so we advised rerunning the model on the rest of the ensembles, following up with a sensitivity analysis that shows the variation in results. See the future work section for more details.

3.3 Scaling wind speed, pressure, and temperature to wind turbine hub height

The output capacity for future wind turbines is expected to reach 17 MW with a growth in hub height to 151 m by 2035 [12]. This design is used as the basis for the turbine model (see Table 1.1 and Figure 1.1). Air density decreases with increasing altitude, leading to a lower momentum extracted from the air by a turbine. The difference between the 151 m hub height

and the standard model output data at 10 m can substantially decrease momentum, which only holds if the increase of velocity due to a change of height is less than the decrease in density. Therefore, this research aims to investigate the mean wind speed, temperature, and pressure by scaling them to a wind turbine hub height of 151 m using empirical relationships [65], [66].

In order to utilise surface wind speed data for investigating the climate change impact on wind turbines, the existing data's 10m height will need to be adjusted based on empirical relationship (equation (3.2)) to match the hub height of the new model [66]. The following relation represents the athematic log function used to scale a 10 m high wind speed to a 151 m hub height wind speed.

$$V_h = \frac{\ln \frac{h}{z_0}}{\ln \frac{z_{data}}{z_0}} \times V_{data} \quad (3.2)$$

Where z_0 is the surface-roughness length in the wind measurement area and is equal to 0.003 for coastal areas or open sea [67]. The difference between surface roughness of 0.003 and the 0.0002 Davenport roughness for water surface for the majority of the EEZ locations is from 0.55 m/s to 0.75 m/s, see Figure 3.6. The 0.55 m/s and 0.75 m/s difference are 4.91% and 6.7% of the rated wind speed of 11.2 m/s, respectively. Which has an implication corresponding to approximately a 14.5 % and 21% increase in kinetic energy flux.

V_h represents the wind speed at height h , the value of h is taken as 151 m, z_{data} is the measured height of the wind speed, equal to 10m. V_{data} is the 10 m wind speed time series. The scaling factor that scales the wind speed V_{data} is equal to 1.33.

The temperature is scaled to 151 m hub height using the following equation [65].

$$T = T_0 - l * (h) \quad (3.3)$$

T_0 : the temperature at sea level, l : is an average constant representing the temperature lapse rate of 0.0065 k/m, and h is the altitude in meters.

The following equation can calculate air pressure for altitudes up to 11 km [65].

$$P = P_0 \left(1 - \frac{l * h}{T_0} \right)^{\frac{g_0 M}{R * l}} \quad (3.4)$$

Where P_0 = static pressure (pressure at sea level) [Pa], T_0 = standard temperature (the temperature at sea level) [K], h = height about sea level 151 m, R = universal gas constant = 8.31 J/ K . mol, and g_0 = gravitational acceleration constant = 9.80665 m/s². M is the molecular weight of air = 0.028 kg/mol.

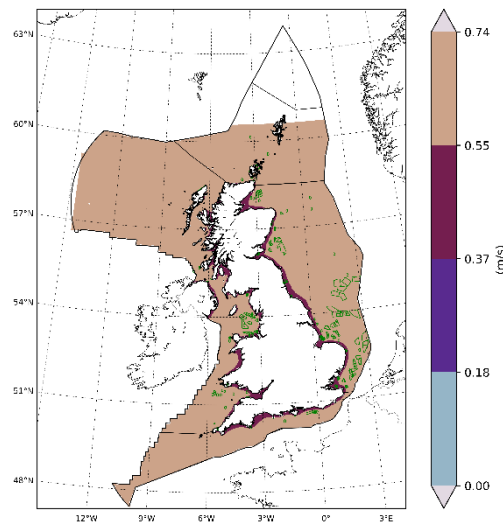


Figure 3.6. The difference between daily wind speed with surface roughness is 0.003 and 0.0002 (m/s).

The scaled temperature and pressure data will be used to calculate the air density in equation (3.5). Based on that, the WPD in Chapter 4 equation (4.1) will be calculated using the air density and the scaled wind speed. An example of a change of air density with height with constant temperature and pressure is seen in Figure 3.7.

$$\rho = \frac{p}{R_{air} \times T} \quad (3.5)$$

Where p is the pressure (kg/m^3) at height h , R_{air} is the specific gas constant for air = 287.05 ($\text{J}/\text{kg} \cdot \text{K}$) [65], [68], and T is the temperature at h .

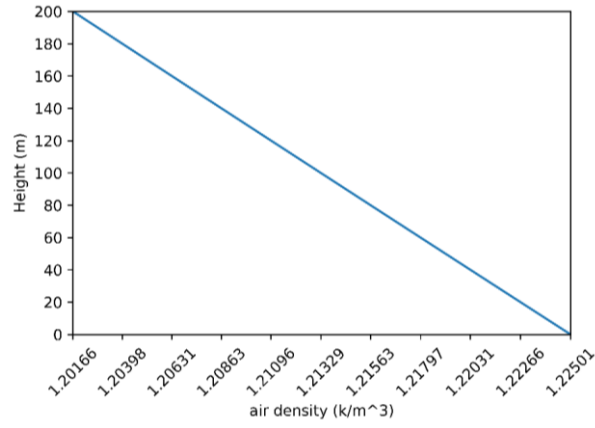


Figure 3.7. Change in air density with respect to height.

3.4 Adopted UK Exclusive Economic Zone regions

The EEZ was established in 1982 during the third United Nations Conference on the Law of the Sea. The EEZ extends up to 200 nautical miles from the coastal baseline [69]. It delineates a maritime area wherein a sovereign state possesses special rights pertaining to various resources, such as wind and water energy production. Figure 3.8 presents the current pre-planning, planning, construction, and operational phases as of October 2023 OWFs.

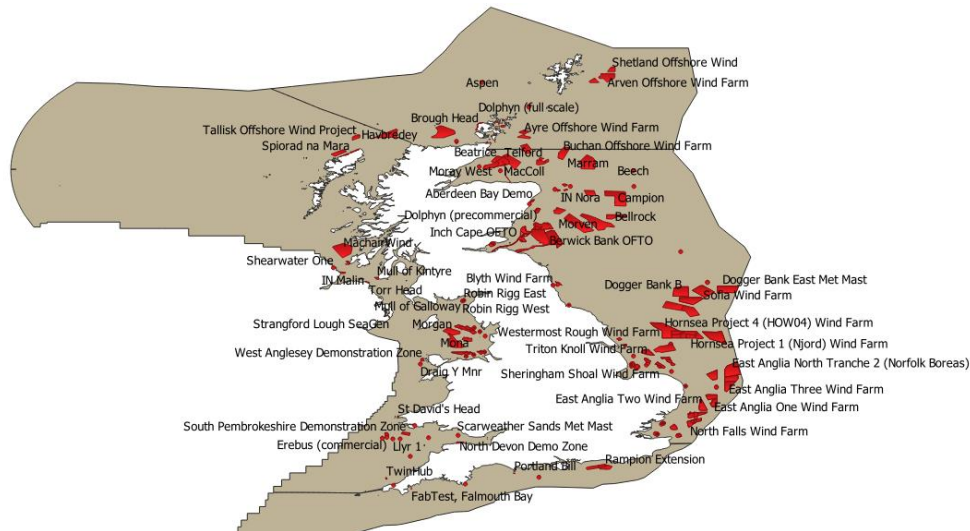


Figure 3.8. Fixed bottom wind farms and floating wind farms in UK offshore area. The data include all pre-planning, planning, construction, and operational phases according to the available dataset [70]², [71].

Historically, the UK marine weather forecasts are produced as shipping forecasts where each shipping area is characterised as a weather area. Since 2002, the UK offshore areas have been divided into 31 shipping forecast areas, as shown in Figure 3.9 [72]. Influenced by these areas, this research used the boundaries of the shipping forecast regions to define four major homogenous wind regions in the UK EEZ based on their locations: East, South, West, and North (see Figure 3.9). Each of the four directions represents the main four areas for offshore wind farm expansion, and the comparison is made to indicate which direction (East, west, north, or south) the future installation will be recommended. The UK's offshore wind strategy is geographically distributed across these four main directions. For instance, the North Sea (East) is one of the busiest regions for offshore wind installations, with substantial capacity already in place. By grouping the shipping regions in this way, we align the analysis with the current bulk installation areas, making it easier to discuss existing infrastructure and planned projects. On the other hand, merging the regions simplifies the presentation of results, making them more

² "Contains data provided by The Crown Estate that is protected by copyright and database rights."

accessible for high-level policy and decision-making. For instance, summarising the outcomes in terms of East, West, North, and South allows stakeholders to focus on broader trends and recommendations, instead of dealing with the complexity of 31 individual shipping regions. The four main regions still respect the existing shipping region boundaries. This ensures that the spatial analysis remains grounded in real-world divisions, which are important for both navigational safety and planning of offshore infrastructure. While the results are summarized for these four broad regions, the detailed spatial analysis of all 31 shipping regions is still accessible. This allows for more granular investigation if needed, offering both a big-picture perspective and specific insights. It ensures that while high-level decisions can be made based on the four regions, more detailed results can be referenced for localized planning or specific project assessments. In conclusion, by aggregating the shipping regions into four main areas, East, West, North, and South we offer a streamlined yet insightful analysis of offshore wind potential, addressing both the current bulk installations and future recommendations. This approach ensures that the results are both easily interpretable for decision-making and rooted in the actual spatial distribution of wind farm activity in the UK.

All four regions have been contoured with the EEZ mask. It should be noted that only available data in UKCP18 intersecting the EEZ has been considered in the analysis. The UKCP18 (2.2 km) is only available in a latitudinal boundary equal to 60.58° N, which does not cover the north region of the EEZ (latitude boundary is 63.5° N). So, the results are truncated at 60.58° N. The West region is the largest and the South region the smallest. The shipping areas included and merged into each region, along with the mean and standard deviation of the wind speed scaled to 151 m hub height using the 1981-2000 scenario, are also given in Table 3.1. The analysis in the thesis is made as a comparison between the four regions.

Table 3.1. The merged shipping areas, and statistics of their wind speed from ensemble 01 using a daily mean hub-height (151m) wind speed dataset (1981-2000 scenario).

Region	Included coastal sea areas	Mean (m/s)	Standard deviation (m/s)
East	Cromarty, Forth, Forties, Tyne, Dogger, Humber, Thames,	9.9	4.7
South	Sole, Plymouth, Portland, Wight, Dover, Fitzroy	9.7	4.5
West	Malin, Hebrides, Irish sea, Lundy, Fastnet, Bailey, Rockall	10.7	5.07
North	Fair isle, Viking, Faeroes	10.8	5.04

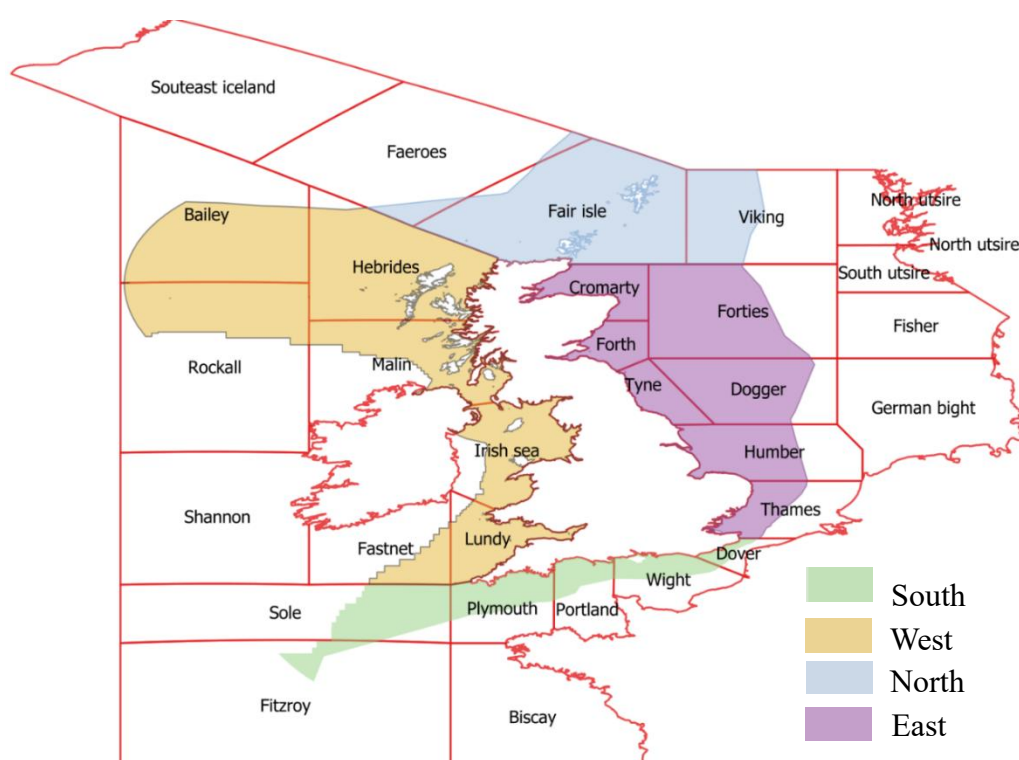


Figure 3.9. The shipping areas are plotted in red lines [72]. The inner boundary (between the green (South), yellow (West), blue (North), and purple (East) regions) are the boundaries for the four considered regions within the EEZ.

The next three chapters (chapter 4, chapter 5, and chapter 6) will describe the considered factors in this research, specifically, a detailed investigation of the future projection of wind power generation, extreme HWE, and extreme LWEs. The results from the following three chapters and the other two economic factors will be fed to MCDA to choose the preferred siting location. As a target, this research aims to inform current decision-makers and wind energy planners of future risks in offshore energy for OWF.

Chapter 4 The long-term impact of climate change on UK offshore wind operations

4.1 Overview

This chapter identifies future wind energy production trends and uses them to select the best exclusive economic zone (EEZ) region for the installation of offshore wind farms (OWF), which will assist in avoiding decreasing power production and assure the stability of wind power in the selected locations. Within this chapter, the analysis uses the relative change (RC) of future periods compared to a historical period as well as the difference between the two future periods and a minimum/ maximum acceptable threshold (MAT) for five factors: wind power density (WPD), capacity factor (CF), the stability of wind power represented in monthly variation (MV), seasonal variation (SV), and coefficient of variation (COV). The spatiotemporal analysis has been interpreted as recommendations for the four main offshore areas in the UK EEZ (East, South, West, and North). The work described within this chapter was submitted to the Journal of Cleaner Production (**Abdelaziz et al. 2025a** from Related Publication section).

4.2 Introduction

Recently, there has been an increase in global concern for climate change impacting future renewable generation, including offshore wind power generation [15], [73], [74]. Studies have been developed to analyse the future potential of wind energy and its variability [75], [76]. Other research has focused on optimising the siting of offshore wind, considering multiple economic, social, and environmental criteria based on historical and current data [77]–[81]. Another branch of OWE research focuses on using future warming scenarios to assess future

wind generation changes. These studies have shown that there is a wide range of location diversity in climate change impacts being positive or negative. For example, warming scenarios have been considered in the French offshore regions to assess wind power potential and intermittency [75]. This has shown that because of the temporal variability of wind power increases in this specific location, the overall impact of climate change on the wind power resource is negligible. Also, in the North Sea, using 0.11° Rossby Centre regional atmospheric model, version 4 [82], the variation of WPD and the maximum 100m wind speed have been analysed by Rusu [82]. The research indicated a relative enhancement of the mean WPD in the 2021-2060 period. In China [35], OWE future changes have been investigated using regional climate simulations that follow the greenhouse gas Representative Concentration Pathway (RCP) 8.5 produced in the CORDEX project. It was found that there will be an increase in future wind energy as well as an increase in wind energy variability. Vu Dinh et al. [73] have investigated the future change in wind energy for the sea of Vietnam using RCP4.5 and RCP8.5 and found a decrease in wind power in the autumn season and an increase in the winter season. The changes to wind resources have been investigated in the UK in [30] to assess future changes in the levelised cost of energy for onshore and offshore wind resources in the UK. They find that the CF has increased or decreased depending on the location by 2100. Long-term analysis using historical climate model data provides an accurate estimation for wind power generation for Qatar's onshore and offshore locations [83], offshore locations in Canada [84], the South region of China [76], and the Iberian Peninsula [85].

From this previous research, we conclude that there is agreement that (a) investigating wind potential using a longer-time period provides a realistic overview of wind energy capacity, (b) combining long-term analysis with future warming scenarios helps to understand the potential changes of wind energy accurately, (c) high-resolution models similar to observation data are highly desirable to capture mesoscale events [40], and (d) different

geographic locations can provide different climate change signals, therefore, diversifying target geographical regions is needed to build inclusive knowledge about future changes in wind energy.

In the long-term future, climate change may impact the wind power potential, consequently influencing electricity system operation and planning. The influence of climate change on wind power production variability is multifaceted. It encompasses both increases and decreases in wind speeds across different locations and time periods, driven by regional climate changes, shifts in seasonal patterns, and the occurrence of extreme weather events. This study aims to comprehensively investigate all wind energy indicators needed to assess the future change in offshore wind potential for regions within the UK EEZ. The contributions of this chapter are summarised as follows:

- We assess the variability in daily temperature and pressure data throughout different seasons within two future time frames, aiming to analyse the consequential effects on future WPD.
- We engage in a comparative analysis of four proposed regions within the EEZ of the UK to identify the most suitable areas for the prospective expansion of wind farms. In this context, the chapter presents two distinct recommendations for future OWF installations. The first recommendation entails repowering existing OWFs by considering the relative change (RC) observed during the two future warming periods compared to the baseline (The recommendation for repowering is based on the direction of change (whether an increase or decrease) between the baseline and future scenarios. The decision is made without considering the specific magnitude of the change but rather based on whether particular factors are expected to improve or decline). This recommendation is particularly relevant in scenarios where future geospatial constraints are anticipated. The second recommendation involves the identification of the best site, relative to all other possible locations within the UK EEZ, for new OWF installations. This determination is made using criteria

encompassing the spatial median trend and the Minimum/ Maximum Acceptable Threshold (MAT).

This chapter is organised as follows: In Section 4.3, investigate the seasonal variation in the daily mean wind speed, pressure, and temperature; using these earlier findings, changes in WPD were then assessed. Section 4.4 describes the methodology used to conduct the analysis. In Section 4.5, the long-term impact of climate change on UK wind production is calculated for five factors (WPD, MV, seasonal variation (SV), COV, and CF). Section 4.6 illustrates the conclusion of the results.

4.3 WPD calculation using temperature and pressure data for air density

This section shows the seasonal variation in daily mean wind speed, pressure, and temperature data used to calculate the air density to show improved accuracy of WPD calculations when compared with using the 1.225 kg/m^3 standard air density value [83], [86], which can only be realised under standard conditions with $T= 15^\circ \text{C}$ and $p= 1013 \text{ hPa}$ at sea level [86].

WPD is an essential indicator for resource assessment, independent of wind turbine characteristics. Wind farms that are installed in a high WPD site produce on average higher electrical power. WPD is calculated using the following equation (4.1) [68], [36].

$$WPD = 0.5 \times \rho \times v^3 \quad (4.1)$$

Where ρ is the air density and v is the wind speed. The WPD calculated using a standard air density value uniformly across the region is compared to the air density calculated from measured pressure and temperature data (real air density) values. In equation (3.5) [68], the pressure and temperature data are used to calculate real air density. The only UKCP18 temporal data common between temperature and pressure are daily and monthly timesteps. Thus, a daily value of air density will be used in all relevant calculations except those usually produced using hourly time steps, such as CF and power output.

4.3.1 Daily mean pressure

Figure 4.1 summarises the potential change in daily mean sea level pressure (MSLP) between the baseline and two future periods. As expected, the MSLP has a wider distribution of values in winter than in summer, reflecting the seasonal cycle. In all seasons, the MSLP distribution has an increased negative skew in the 2061-2080 period compared to the baseline. The two future periods show a negligible change compared to the baseline in distribution tails.

4.3.2 Daily mean temperature

Figure 4.2 shows an increase in daily temperature for all seasons in 2021-2040 and 2061-2080. The outliers in the figure were not removed from the data as in temperature datasets; outliers often represent real weather conditions, such as heatwaves. Since wind power density calculations depend on temperature and wind speed, removing outliers could lead to an inaccurate representation of real-world conditions, particularly when assessing long-term wind energy potential. The summer and autumn seasons have a maximum value of approximately ($\sim$) 293K for the historical period. In comparison, the 2021-2040 and 2061-2080 periods have a noticeable shift in the distribution's right tail, reaching $\sim$ 296K and 300K, respectively. Also, the 2061-2080 period has a maximum value of $\sim$ 290K in the winter and spring seasons. The box plot shows an increase in the median daily mean temperature for the two future periods for all seasons. The climate change signal for temperature data in future periods is more pronounced than the pressure data. From the ideal gas law equation (3.5), if there are no changes in other parameters, a temperature increase with equal pressure will decrease air density in future periods, leading to a decrease in WPD.

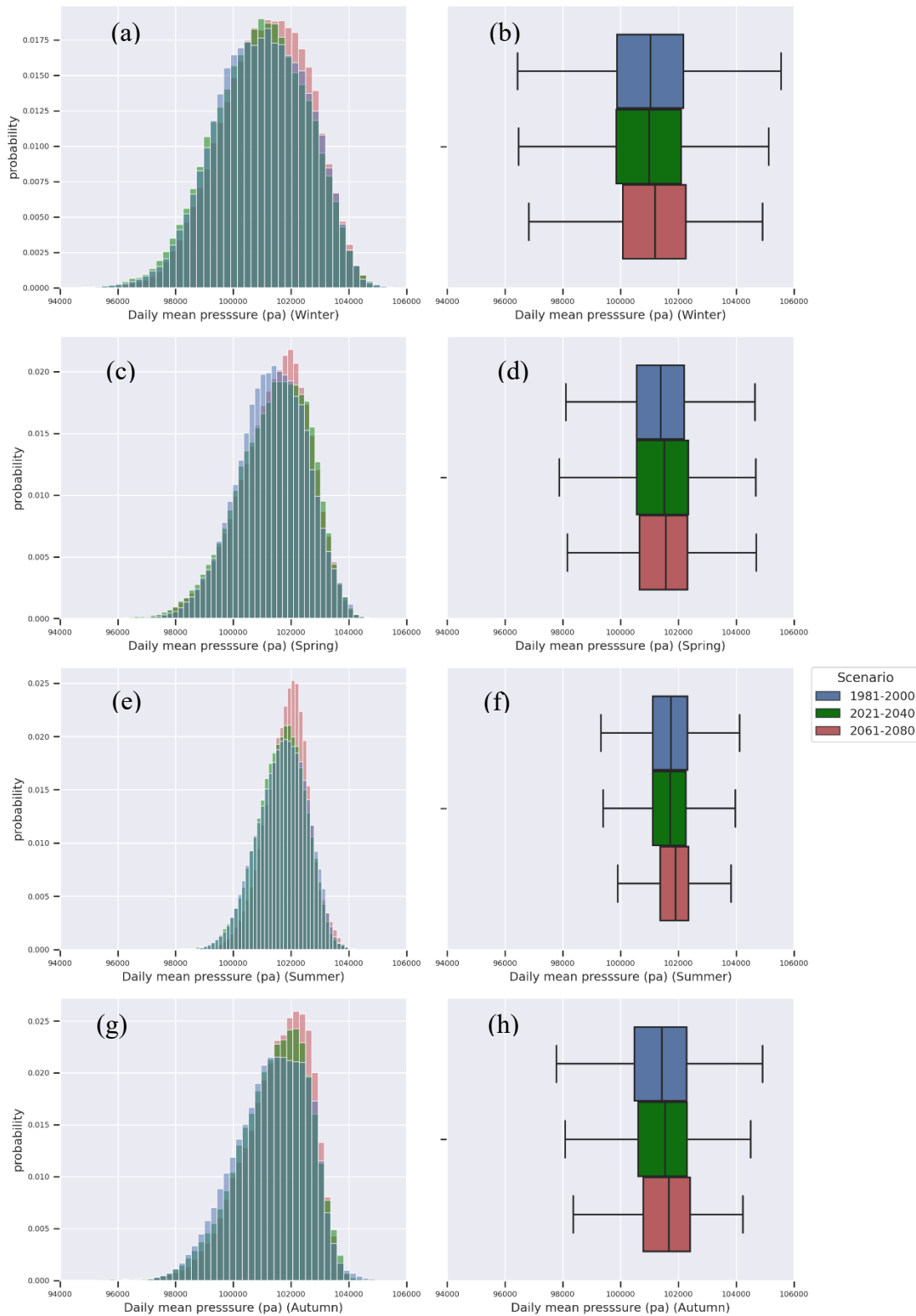


Figure 4.1. Using daily sea level pressure data in (Pa), the histogram in the first column, and the boxplot in the right column, each row represents a season, starting from winter, spring, summer, and autumn, respectively. The three climate periods (1981-2000 (blue), 2021-2040 (green), and 2061-2080 (red)). The box holds the interquartile ranges (IQR), and the midline represents the median. The whiskers show the maximum and minimum values. The thin horizontal black line represents the rest of the distribution.

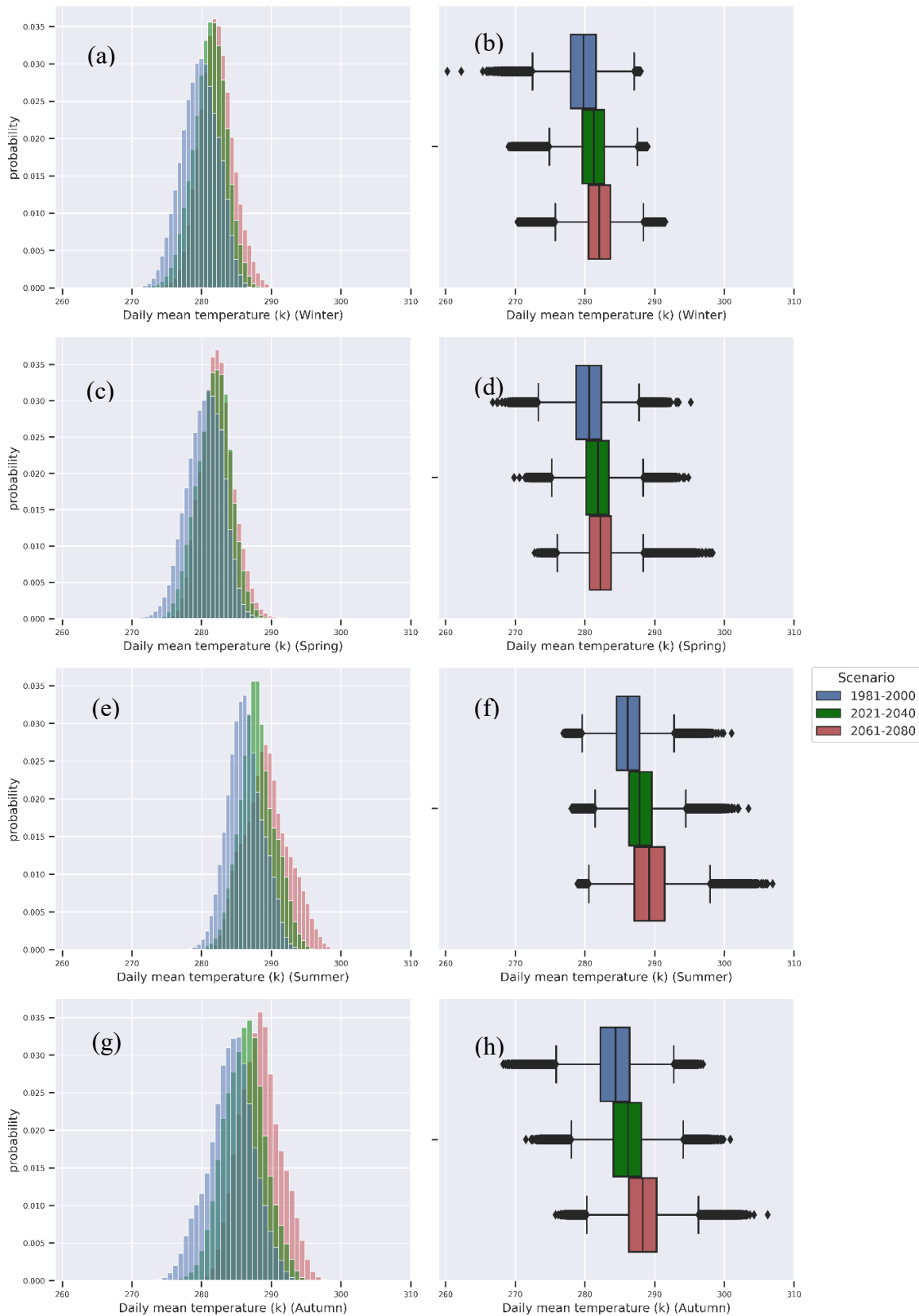


Figure 4.2. Histogram and boxplot using daily mean temperature data in (k), each row represents a season, starting from winter, spring, summer, and autumn, respectively. The three climate periods (1981-2000 (blue), 2021-2040 (green), and 2061-2080 (red)). The box holds the interquartile ranges (IQR), the midline represents the median. The thin horizontal black line represents the rest of the distribution. The whiskers show the maximum and minimum values. The points beyond the thin horizontal lines are outliers.

4.3.3 Daily mean wind speed

Using the daily mean wind speed dataset, Figure 4.3 shows seasonal variation in hub height wind speeds across all three-time windows, with the existing planned OWF locations also marked (see Figure 3.8 for the names identifying the currently installed OWF in the map). Seasons in UKCP18 are described as winter (December, January, February), spring (March, April, May), summer (June, July, August), and autumn (September, October, and November), which are meteorologically accepted seasonal categories [87]. Figure 4.3, column (a), displays the historical period's daily mean for each season. During the winter, the highest seasonal wind speed between 12 m/s to 14 m/s is located above latitude 54° N, while the lowest wind speed range is between ~ 6.3 m/s to 9.7 m/s, which occurs in the summer. Mean wind speed in autumn and spring varies from ~ 10 m/s to 12 m/s across all regions in the EEZ. For all seasons, mean wind speed gradually decreases from north to south. 2021-2040 relative to 1981-2000 is shown in Figure 4.3, column (b). The East and North regions have the largest increase in mean wind speed in spring, with up to 5% increase in mean wind speed. Also, in Figure 4.3 column (c), 2061-2080 relative to 1981-2000 shows the East region has the largest increase in mean wind speed in winter and spring. Also, the West region's largest increases occur in the winter season. During summer, all regions show a decrease in mean wind speed ranging from ~ 1 - 8% in 2021-2040 to ~1 - 10% in the 2061-2080 period relative to the baseline period. It is worth noting that the mean wind speed is used to understand the future trend in wind speed for each location in the UK EEZ. For each cell grid, the mean of 20 years for each of the four seasons is calculated for that purpose.

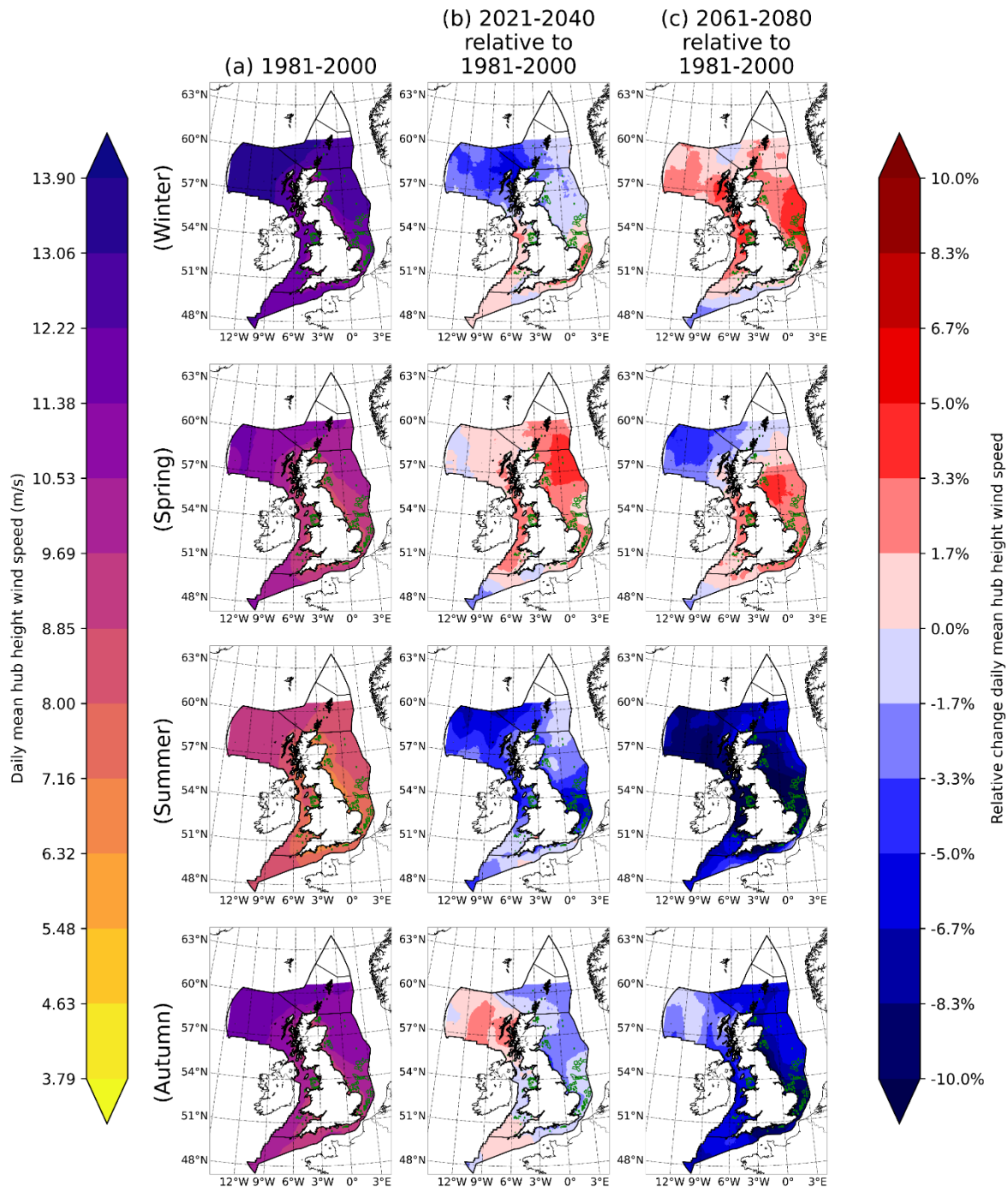


Figure 4.3. Spatial map representing daily mean wind speed in baseline and two future periods for four seasons, rows from 1 to 4 represent the four seasons: winter, spring, summer, and autumn. Columns (a) show 1981-2000, column (b) 2021-2040 relative to 1981-2000, and column (c) 2061-2080 relative to 1981-2000. Black outer boundaries represent the EEZ, and black internal boundaries represent four regions considered in the study. The green lines represent the fixed bottom wind farms and floating wind farms in UK offshore area. The data include all pre-planning, planning, construction, and operational phases [70], [71].

4.3.4 Real and standard WPD calculations

The real air density was calculated using equation (3.5) at 151 m hub height for the 1981-2000 period is shown in Figure 4.4 (a). Figure 4.4 (b) shows the RC between the real air density and the commonly used standard value of air density (1.225 kg/m^3). The North-South air density gradient decreases from 1.3% to -0.4%.

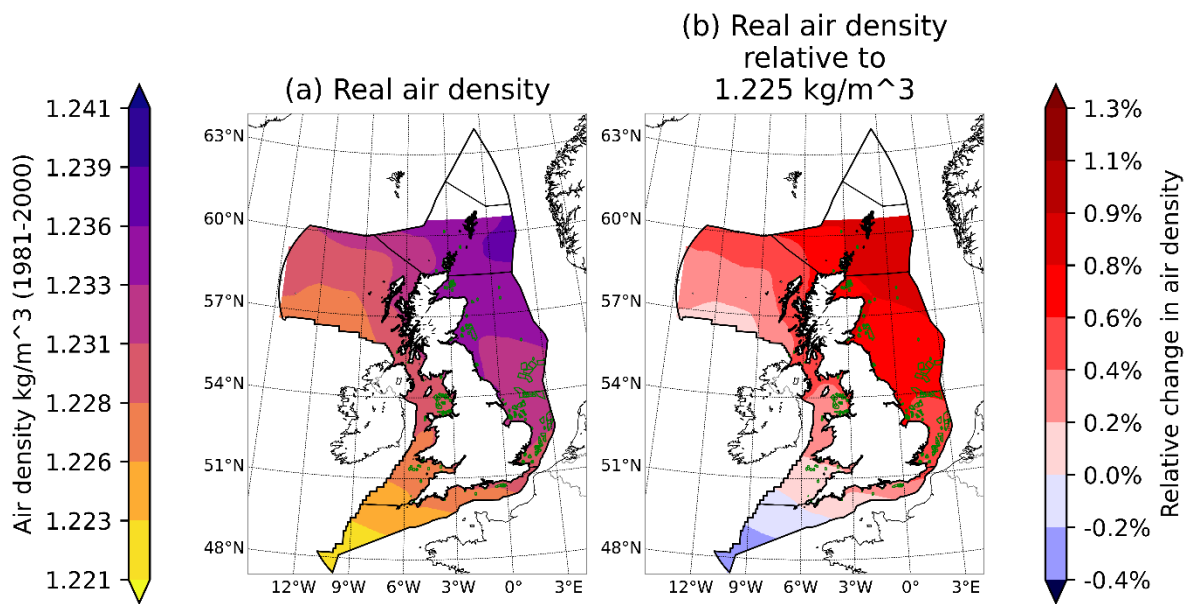


Figure 4.4. (a) Air density using pressure and temperature data (kg/m^3) at 151 m hub height. (b) Relative change air density using pressure and temperature data against 1.225 kg/m^3 standard air density. The data used for both plots are the 1981-2000 period (the four seasons collectively). Black outer boundaries represent the EEZ, and black internal boundaries represent four regions considered in the study. The green lines represent the fixed bottom wind farms and floating wind farms in UK offshore area. The data include all pre-planning, planning, construction, and operational phases.

These variations in air density in the different regions and periods imply that the WPD calculated using standard air density will be underestimated in the northeast of the EEZ. Figure 4.5 shows the difference between WPD calculated with real air density and the standard value of air density for each season using the baseline period. The RC calculation shows decreasing WPD values from north to south, similar to the decreasing real air density than standard air density from north to south (Figure 4.4). The relative seasonal change between real and standard WPD calculations results in a positive change in the northeast locations (see Figure

4.5). The largest changes are in the winter and spring seasons, with an up to 1.7% increase in RC. In the summer and autumn, there is a decrease from north to south from 0.4% to -1.6%. It is essential to consider temperature and pressure data while calculating the WPD. There is a seasonal range of change between $\sim -1.6\%$ and 1.7% when using real air density against standard air density.

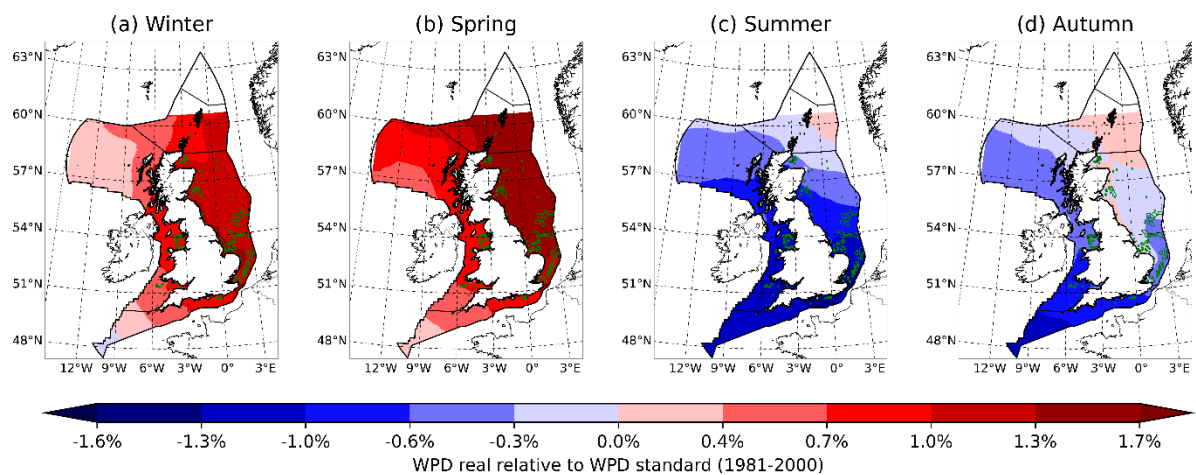


Figure 4.5. Relative change between seasonal wind power density (WPD) calculated using air density with pressure and temperature data and (WPD) calculated using 1.225 kg/m^3 air density. (a) Winter, (b) Spring, (c) Summer, (d) Autumn. The data used for both plots are the 1981-2000 period. Black outer boundaries represent the EEZ, and black internal boundaries represent four regions considered in the study. The green lines represent the fixed bottom wind farms and floating wind farms in UK offshore area. The data include all pre-planning, planning, construction, and operational phases.

4.4 Methods

This chapter presents the analysis of key factors pertaining to wind energy, including WPD, CF, and stability assessments of wind power generation (namely MV, SV, and COV). Investigating these factors and their potential future changes could significantly aid in mitigating the current constraints on electricity resources.

4.4.1 Relative change (RC) in future periods to the historical period

The RC in each factor between future and historical periods are calculated using equation (4.2).

A positive/negative indicator is constructed for each factor based on the ability to enhance wind production in the future.

$$RC = \frac{(V_j - V_i)}{V_i} \times 100 \quad (4.2)$$

Where RC is the relative change in percentage unit (%), V_j is the final value (two future periods), and V_i is the initial value using the historical period.

For each region/ period, the positive, negative, and zeros counts have been calculated from each factor's RC calculation. Normalising the three final positive, negative, and zeros values gives a ratio of three numbers representing one period in a specific region. For example, in the spring season, the results of WPD RC between 2021-2040 and the 1981-2000 periods in the North region have positive, negative, and zero values. The count of positive, negative, and zeros has been normalised, so the resulted ratio of three numbers is similar to (positive = 97.7%: negative = 2.3%: zero = 0.0). The final positive, negative, and zero ratios are now used to compare the North region against the other three regions in the same period (2021-2040 relative to 1981-2000). The comparison depends on the factor type. The positive change is considered the required indicator for the WPD and CF in the RC calculations (profit factors). At the same time, the negative change is the indicator necessary for MV, SV, and COV (cost factors), see Figure 4.6. In Figure 4.6, the red hash line refers to factors WPD monthly variation, WPD seasonal variation, and COV that consider negative RC favourable for future siting in a region. The bold yellow line refers to the factors (CF and WPD) that consider positive RC favourable for future siting in a region. For example, in the case of WPD calculation, we are looking to increase the ratio of positive values to negative values (indicator $\uparrow$). The more advantageous region will have a distinct increase in positive values compared to negative values (increase WPD in the future compared to the historical period).

The result from this calculation shows three types of recommendations: strong, weak, and no recommendation. For example, in Table 4.2, the strong recommendation is chosen in the spring season when the ratio in WPD (Increasing positive values is recommended ↑) in the North region is 97.7%: 2.3%: 0.0 and in the East region 99.3%: 0.7%: 0.0 in 2021-2040 relative to the 1981-2000 period. At the same time, the corresponding ratio for the other two regions has a pronounced increase in negative values compared to positive values. In this example, the North and East regions have been chosen as the most desirable region according to the WPD factor. In case of weak recommendation (Increasing negative values is recommended ↓). If a region has a ratio equal to 94.9%: 5.1%: 0.0 and the other three regions have the same ratio equal to 100%: 0.0: 0.0. In this case, all results are considered undesirable as the number of positive values is pronouncedly increasing, only one region has a slight increase in negative values, but still the number of positive values is large. In the no recommendations case, all compared results have an increased risk, and there are no changes when comparing the four regions. For example, in Table 4.5, for SV (decreasing number of positive values is recommended ↓), when comparing all regions in 2061-2080 relative to the 1981-2000 period, we have 100%: 0.0: 0.0 in all regions. This case means a consistent increase in risk in the future period relative to the baseline period, so a (--) mark is used to indicate this case for all regions (see Table 4.2, Table 4.5, Table 4.7, and Table 4.9). An overview of the mentioned methodology is in Figure 4.6.

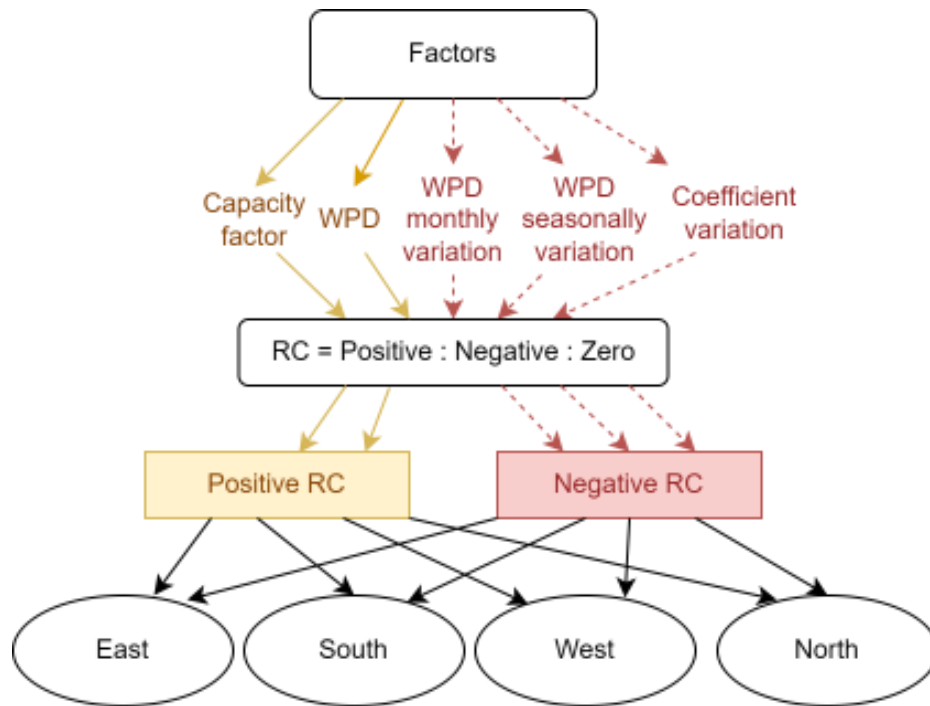


Figure 4.6. Schematic overview for choosing the recommended region based on quantifying the relative change for all factors concerning the historical period. RC is the relative change.

4.4.2 Minimum/ maximum acceptable threshold (MAT)

The MAT corresponding to each factor is chosen from literature to identify the threshold between the acceptable and unacceptable range; see Table 4.1. The difference between MAT and the regional median of the two future periods corresponding to each factor is used as the primary tool in this analysis for region recommendation. Moreover, the region median and 25-75% interquartile ranges (IQR) are used to summarise the spatial calculations for all factors. In Table 4.3,

Table 4.6, Table 4.8, and Table 4.9, the 2021-2040 and 2061-2080 periods relative to the MAT for each factor considered are calculated. For instance, the following steps are taken to determine the recommended region for siting OWF through CF calculations: 1) The median CF value is calculated for each of the four regions, 2) The difference between median CF and 20% MAT is calculated, and 3) The region with the largest difference between the median and

MAT is then considered the recommended region for the given period. In the case of MV, SV, and COV, the largest difference from the 1.75 threshold is sought. This can be seen in SV analysis, see Figure 4.11 (b), where the orange vertical arrow points to the West region's median (indicating the largest difference from the 1.75 threshold in the 2021-2040 period compared to the other three regions). The (✓✓) is used in this case to indicate the recommended sites. We identify MAT as the minimum acceptable threshold when using factors CF and WPD, as any higher values than the thresholds are considered in an acceptable range. On the other hand, we identify MAT as the maximum acceptable threshold when using factors MV, SV, and COV, as any lower values than the thresholds are considered in an acceptable range.

Table 4.1. MAT for wind energy production factors.

Factor	MAT	Acceptable	Undesirable	Ref
		range	range	
WPD (kW/m^2)	0.2	≥ 0.2	< 0.2	[35], [88]
MV, SV, and COV	1.75	≤ 1.75	> 1.75	[35], [34]
CF	20%	$\geq 20\%$	$< 20\%$	[88]

4.5 Wind production analysis

This section shows the results for all factors (WPD at wind turbine hub height and its stability, WPD classes, and CF) included in the investigation for future wind production changes.

4.5.1 Wind power density

Figure 4.7 shows WPD at wind turbine hub height for the baseline period and the changes for the two future climate periods. In the 1981-2000 period (see Figure 4.7, column (a)), the lowest range of WPD is found in the summer season, near the coastline, from 0.11 to 0.54 kW/m^2 . While the highest range is found in winter season, in the northwest of the EEZ, from 2.19 to

2.54 kW/m². In Figure 4.7, columns (b) and (c), the RC between the 2021-2040 and 2061-2080 periods to the 1981-2000 period is calculated, respectively. The figure shows a decrease (of between 10% to 40% (see Figure 4.7 (b), (c) for summer). Also, in the autumn season, the 2061-2080 period has a pronounced decrease in all regions from 10% to 40%. On the other hand, an increase (up to 20%) in WPD was found in the spring season for all regions in the 2021-2040 period, also below latitude 57° N in the 2061-2080 period. Moreover, in winter season the 2061-2080 period has up to 20% increase in locations above latitude 51° N. RC calculations in Figure 4.7 columns (b) and (c) (showing positive, negative, and zero values) is transformed in Table 4.2 to three numeric ratios for each of the four regions as discussed before in section 4.4.1 to determine the most desirable region in each period/ season. Table 4.2 calculates the RC for all sites in the two future periods corresponding to the historical period for WPD. The (↑) indicator refers to WPD as a profit factor where the increasing number of positive sites (resulting from the RC calculation) indicates a more advantageous region. East and North regions show strong recommendations in the spring season for the 2021-2040 period. In addition, the East region is recommended in the 2061-2080 period, where most locations exhibited a positive change compared to the historical period. Also, the three climate periods in the East region hold a smaller range of WPD compared to the West region. Accordingly, we rely on the MAT analysis below to determine the final recommendation for the most suitable region for siting future OWF in the UK EEZ.

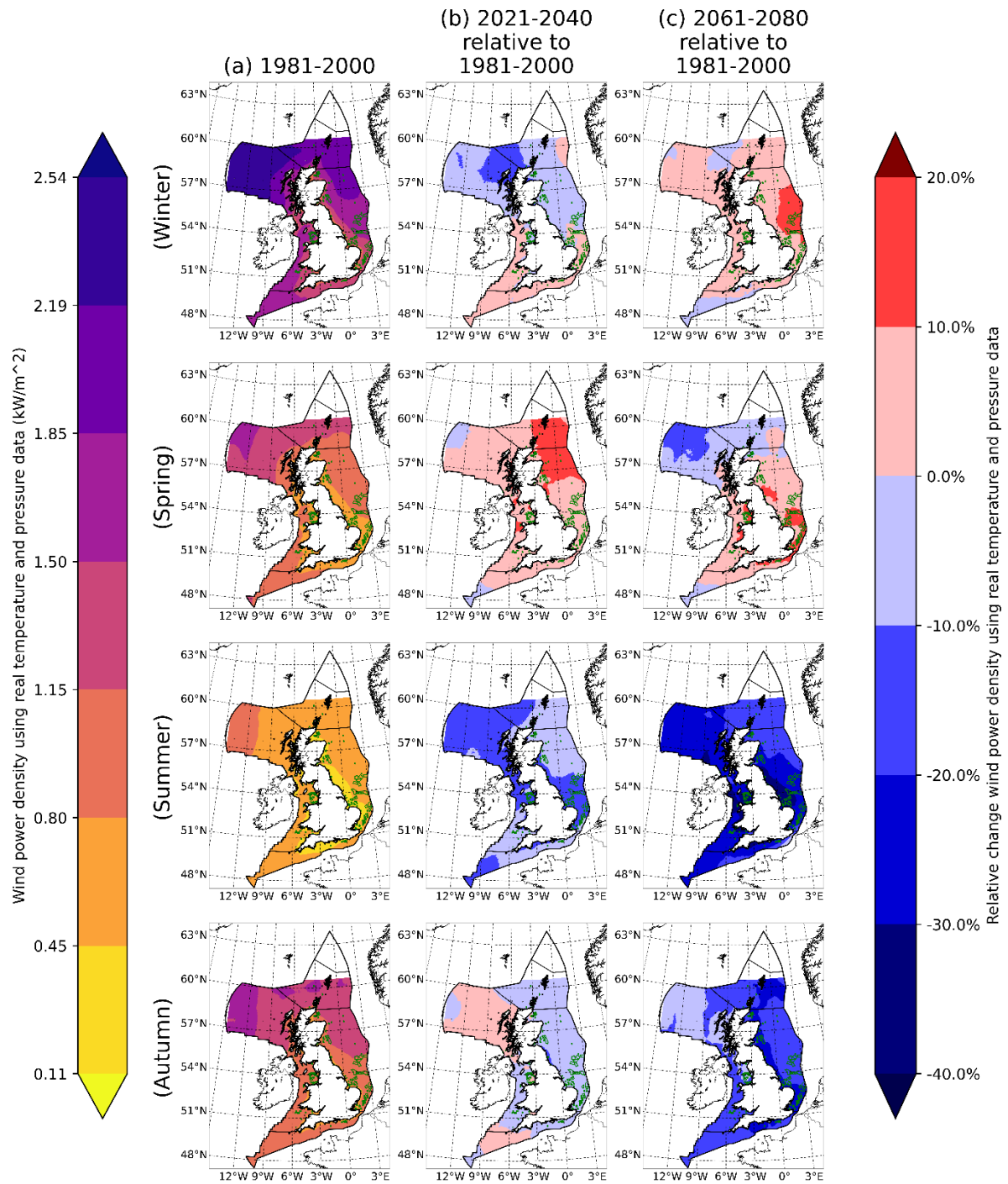


Figure 4.7. A spatial map representing WPD calculations using real pressure and temperature data, rows from 1 to 4 represent the four seasons: winter, spring, summer, and autumn, respectively. Column (a) shows 1981-2000, column (b) 2021-2040 relative to 1981-2000, and column (c) 2061-2080 relative to 1981-2000. Black outer boundaries represent the EEZ, and black internal boundaries represent four regions considered in the study. The green lines represent the fixed bottom wind farms and floating wind farms in UK offshore area. The data include all pre-planning, planning, construction, and operational phases.

The effects of three climate periods on WPD (derived using real air density) for each region and season are summarised in Figure 4.8. WPD decreases consistently under the two future climate periods across all four regions during summer and autumn. This increases energy production risk in these seasons with future climate change. For example, during summer, the East region for the 1981-2000, 2021-2040, and 2061-2080 periods have a region median for WPD equal to 0.6 kW/m^2 , 0.5 kW/m^2 , and 0.4 kW/m^2 respectively. In autumn, for the same region and three periods, the median is equal to 1.3 kW/m^2 , 1.2 kW/m^2 , and 0.9 kW/m^2 , respectively. Moreover, the 2021-2040 period changes during winter also show a reduction in WPD for all regions compared to the baseline period. However, this appears to recover in the East, North, and West regions under the 2061-2080 period.

The 0.2 kW/m^2 is the MAT for WPD; Figure 4.8 show the difference between the region median and 0.2 kW/m^2 to set the recommended region for future siting as described earlier in section 4.4.2. The recommendations are summarised in Table 4.3 for all seasons in the WPD factor. In the 2021-2040 and 2061-2040 periods, for the four seasons, the West region shows the largest difference to MAT for the two future periods (showing a promising result for high WPD).

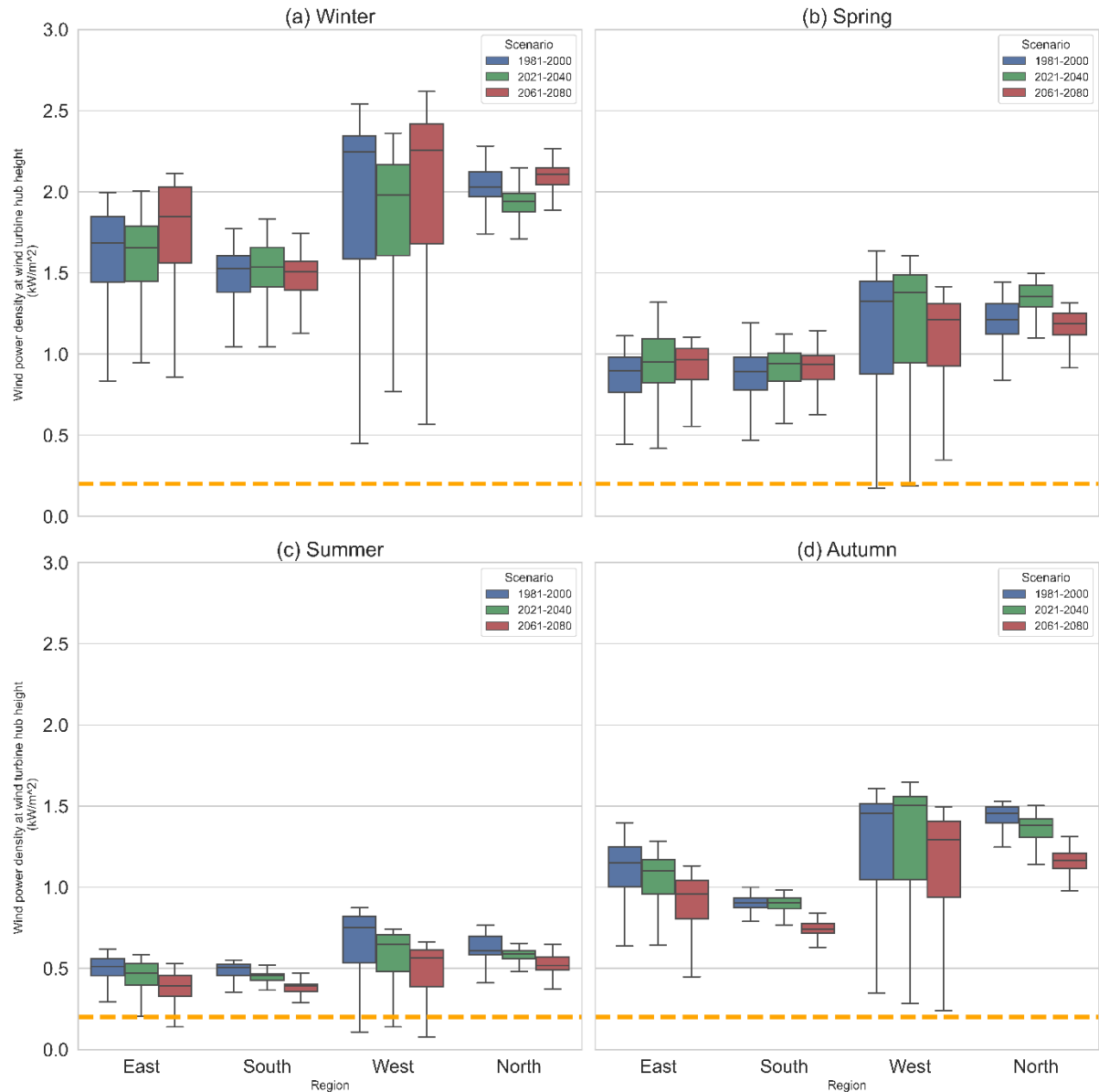


Figure 4.8. Box plot of wind power density (WPD) in kW/m^2 for three periods (1981-2000 (blue), 2021-2040 (green), and 2061-2080 (red)) among all seasons, (a) winter, (b) spring, (c) summer, and (d) autumn. Each plot's four comparison panels for the four regions, East, South, West, and North. The horizontal orange line indicates the 0.2 kW/m^2 minimum acceptable threshold (MAT). The box holds the interquartile ranges (IQR), the midline represents the median. The thin vertical black line represents the rest of the distribution. The whiskers show the maximum and minimum values.

Table 4.2. Region's recommendations for future change relative to the historical period, according to wind power density (WPD).

WPD	Indicator	2021-2040 relative to 1981-2000				2061-2080 relative to 1981-2000			
		East	South	West	North	East	South	West	North
Winter			✓✓			✓✓			
Spring	↑	✓✓			✓✓	✓✓			
Summer		--	--	--	--	--	--	--	--
Autumn				✓		--	--	--	--

Table 4.3. Wind power density (WPD) regions recommendations according to the maximum absolute value.

WPD	2021-2040 relative to 0.2 kW/m ²				2061-2080 relative to 0.2 kW/m ²			
	East	South	West	North	East	South	West	North
Winter			✓✓				✓✓	
Spring			✓✓				✓✓	
Summer			✓✓				✓✓	
Autumn			✓✓				✓✓	

✓✓: Strong recommendation, ✓: Weak recommendation, --: No recommendation, ↑: Increasing, ↓: decreasing.

4.5.2 WPD classes

Eight WPD classes were adopted from [89] to assess wind resources at 10 m height (see Table 4.4). The areas classified in classes less than Class 3 are considered either unsuitable or marginal for wind turbine applications, and locations $\geq$ Class 3 are deemed ideal for wind power production [89].

Table 4.4. Wind power density (WPD) classes [89].

Wind power class	Wind power density (W/m ²)
1	0-100
2	100-150
3	150-200
4	200-250
5	250-300
6	300-400
7	400-1000
8	>1000

Figure 4.9 maps WPD classes for the baseline period along with the changes for the two future climate periods. In the 1981-2000 period (see Figure 4.9, column (a)), the majority of WPD classes in spring and autumn range from 6 to 7 and even extend to Class 8 in winter, while the majority of WPD classes in summer season is generally lower, from 1 to 5. In Figure 4.9, column (a), the Lowest WPD classes in summer are found near the shore in Tyne, Humber, and Thames shipping regions, lower wind speed is usually expected inshore compared to open sea areas. In winter, the Northwest of the UK is the only region with Class 8. In Figure 4.9, columns (b) and (c), the difference between the 2021-2040 and 2061-2080 periods to the 1981-2000 period is calculated, respectively. The analysis shows that, in the two future periods, coastal locations between latitude 51°N and 57°N in the East and West regions during the spring season exhibit a one class increase in WPD. In the summer season, there is a decrease in WPD classes of one class in the 2021-2040 period. This decrease extends to cover the majority of locations in the EEZ in the 2061-2080 period with up to two class decrease. In the winter, spring, and autumn seasons, the majority of locations experience no change in class in both future periods compared to the historical period. In the autumn season, in the 2021-2040 period near coast locations, and in the 2061-2080 period there is a vast area with a one to two class drop below latitude 55°N.

It should be noted that regions with abundant wind power do not necessarily implicate stable wind power. For policymakers, it is essential to consider WPD stability to evaluate the attracted location for future OWF siting.

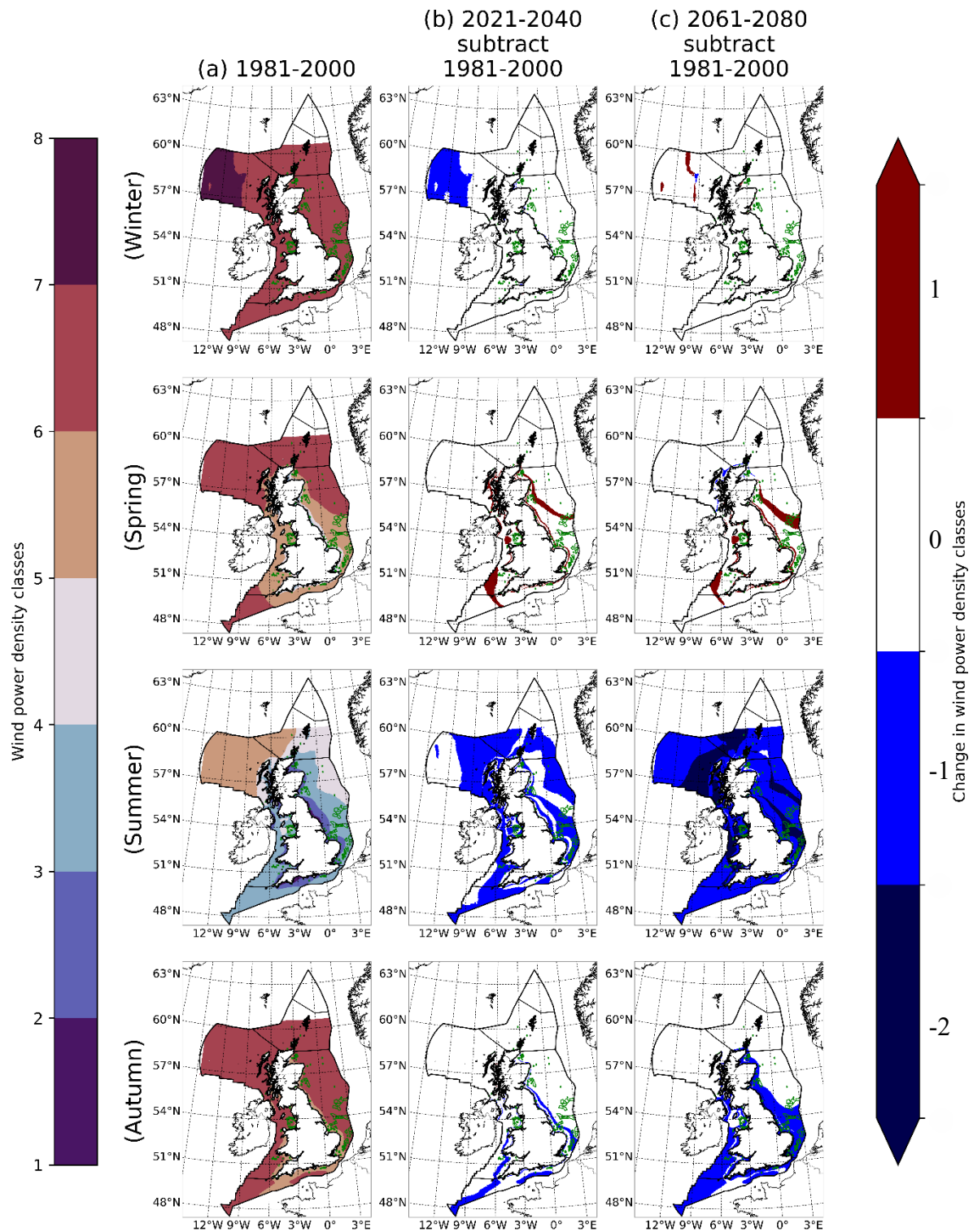


Figure 4.9. Spatial map representing wind power density (WPD) classes, rows from 1 to 4 represent the four seasons, winter, spring, summer, and autumn, respectively, and column (a) shows the climate periods 1981-2000, column (b) 2021-2040 - 1981-2000, and column (c) 2061-2080 - 1981-2000. Black outer boundaries represent the EEZ, and black internal boundaries represent four regions considered in the study. The green lines represent the fixed bottom wind farms and floating wind farms in UK offshore area. The data include all pre-planning, planning, construction, and operational phases.

4.5.3 Monthly variation, seasonal variation, and coefficient of variation

Investigating wind power production variability is essential to achieve a consistent and predictable electricity supply to meet demand. The WPD variability can lead to problems balancing the electrical grid, impact the produced electricity usage, and thus lower wind farm lifetime [90] and profitability [91]. The projected fluctuation of WPD from year to year and seasonally can increase the levelised cost of wind energy [30]. Since the long-term trend in WPD is our aim to support long-term spatial planning, we have used the three matrices MV, SV, and COV, following [92], [93]. An unstable WPD can lower conversion efficiency. Stability can be assessed using the statistics MV and SV obtained from the WPD data. The SV and MV index is used to provide in a single value, a convenient measure of the seasonal/monthly variability of the wind energy resource. Where S_j is the mean wind power for the most energetic season/ month, and S_i is the mean wind power for the least energetic season/ month. The SV parameter effectively quantifies the variability of the wind energy resource relative to its mean level on a 3-month seasonal time scale or a monthly scale using the MV. However, it's important to understand that these variations do not necessarily translate to usable energy due to the constraints imposed by the turbine's power rating. High wind speeds are beneficial, but their full potential can only be realised if the turbines can operate within their rated capacity. On the other hand, derating is an acceptable strategy used to mitigate the impact of high variability and enhance the overall performance and reliability of wind turbines. The stability of the wind power generation resource was analysed using MV, SV, and COV [92]. All three indices give a broad view of the degree of stability on a monthly and seasonal level. The smaller the MV, SV, and COV values, the more stable the monthly WPD is in the location. MV and SV are calculated using the following formula:

$$MV \text{ or } SV = \frac{(S_j - S_i)}{\bar{A}} \quad (4.3)$$

Where MV is the monthly variations index, and SV is the seasonal variation index. S_j is the magnitude of WPD in a month/ season with the highest WPD in a year. S_i is the magnitude of WPD in month/ season with the lowest WPD in the same year. $\bar{A}$ is the annual average WPD.

In Figure 4.10, rows 1 and 2, the MV and SV spatiotemporal variability of the corresponding WPD are estimated, respectively. In MV calculations, Figure 4.10 columns (b) and (c), there is an increase in the two future periods for all regions except the South region, ~ up to a 10% decrease in the 2061-2080 period compared to the baseline period. Also, there is a decrease in the north of the West region in the 2021-2040 period, up to ~ 10%, indicating an increasing wind power stability in these regions. The most affected shipping regions by the increase in MV are the Forties, Dogger, and Humber in the East region and Malin, Irish Sea, and Lundy in the West region. Table 4.5 summarises the MV and SV spatial RC calculations shown in Figure 4.10, columns (b) and (c). The ($\downarrow$) indicator refers to MV and SV as a cost factor where the decreasing number of positive sites (resulting from the RC calculation) indicates a more advantageous region. In 2021-2040, SV strongly recommends the North region, while the South region is recommended in the 2061-2080 period.

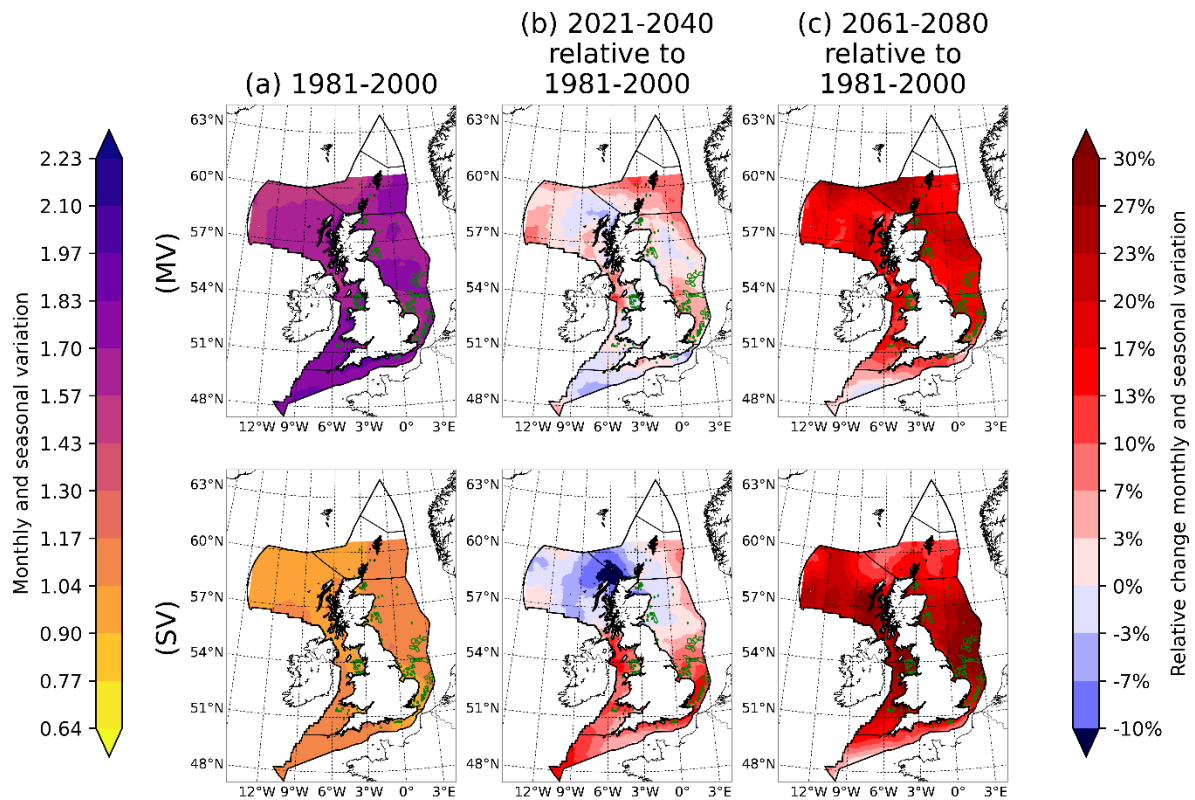


Figure 4.10. Row 1 shows the monthly variation (MV) index, and Row 2 offers the seasonal variation (SV) index. The three figures represent (a) 1981-2000, (b) 2021-2040 relative to 1981-2000, and (c) 2061-2080 relative to 1981-2000. Black outer boundaries represent the EEZ, and black internal boundaries represent four regions considered in the study. The green lines represent the fixed bottom wind farms and floating wind farms in UK offshore area. The data include all pre-planning, planning, construction, and operational phases.

Figure 4.11 shows the median and IQR of all regions for (a) MV and (b) SV. The extreme values in boxplot distribution calculation are an outlier if it is at least 1.5 IQR below the first quartile and above the third quartile. As this chapter focus on wind power production, not on the extremes, the IQR and the median values will be considered, and we will not focus our description on the extreme values. Generally, the range of MV is greater than SV. The 1.75 threshold is the MAT for the MV and SV analysis; see Table 4.1. $MV \leq 1.75$ is desirable, as it is an indicator of stable wind production [35], [34]. In MV analysis, see Figure 4.11(a), the West region has the smallest region median compared to other regions, so it has the smallest difference between its median and MAT in the 2021-2040 period, which imposes the least risk for unstable power production in the region. In the 2061-2080 period, the South region has the

smallest region median compared to the other areas in the same period. Although the South region is considered the most favourable compared to the other regions, the region median still has a value > 1.75 , indicating unstable wind production. Using SV analysis, for 2021-2040 relative to the MAT, the West region has the largest difference to MAT (indicated by the vertical orange line in Figure 4.11 (b)), and the South region has the largest difference in 2061-2080 relative to the MAT. Generally, the SV shows more promising values compared to MV analysis (all region median is ≤ 1.75), see Table 4.6 for the recommended regions based on the distance to the 1.75 MAT.

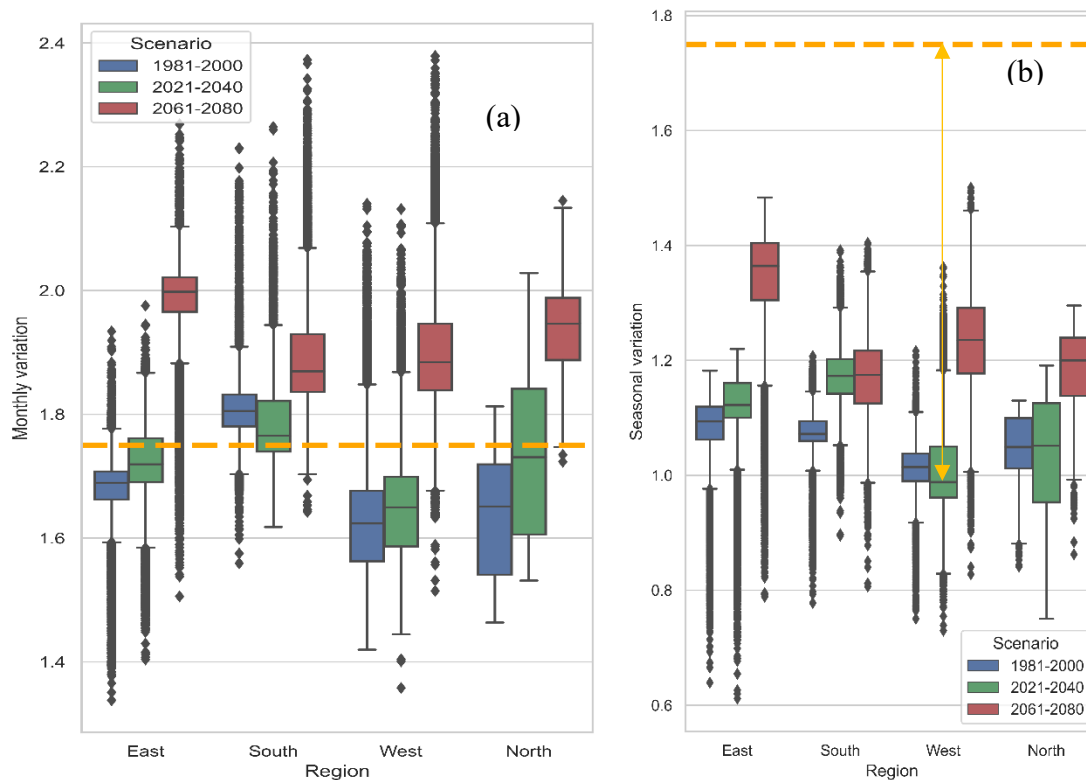


Figure 4.11. Box plot for (a) Monthly variation (MV), (b) seasonal variation (SV), showing variation for the four regions East, South, West, and North. (1981-2000 (blue), 2021-2040 (green), 2061-2080 (red)). The horizontal orange line indicates the 1.75 maximum acceptable threshold (MAT). In (b), the vertical orange line points to the difference between the 1.75 and the median of SV (2021-2040 period) in the North region. The box holds the interquartile ranges (IQR), the midline represents the median. The thin vertical black line represents the rest of the distribution. The whiskers show the maximum and minimum values. The points beyond the thin vertical lines are outliers.

Table 4.5. Region's recommendations for future change relative to the historical period, according to monthly variation (MV) and seasonal variation (SV).

Factor	Indicator	2021-2040				2061-2080			
		relative to				relative to			
		1981-2000				1981-2000			
		East	South	West	North	East	South	West	North
MV	↓		✓✓				✓✓		
SV	↓				✓✓	--	--	--	--

Table 4.6. According to the maximum absolute value, monthly variation (MV) and seasonal variation (SV) region recommendations.

Factor	2021-2040				2061-2080			
	East	South	West	North	East	South	West	North
MV			✓✓			✓✓		
SV			✓✓			✓✓		

✓✓: Strong recommendation, ✓: Weak recommendation, --: No recommendation, ↑: Increasing, ↓: decreasing.

The volatility of the wind power resource is assessed on a seasonal scale using the equation (4.4). The COV relies on the standard deviation and the mean wind speed.

$$COV (Winter - Spring - Summer - Autumn) = \frac{\sigma}{\bar{a}} \quad (4.4)$$

Where *COV* is the coefficient of variation calculated separately for the four seasons, σ is the standard deviation, and $\bar{a}$ is the mean, both calculated over the season. In Figure 4.12, the two future periods show up to 40% positive change, indicating an increased risk of unstable wind power compared to the historical period. It is worth mentioning that turbine control systems are designed to manage the operation of wind turbines in response to varying wind conditions, thereby minimising fluctuations in power output, which plays an important role in smoothing WPD. See Table 4.7 for a summary of recommended regions chosen based on the percentage of cell grids with a negative change in the future, where the South and East regions are dominant in most recommendations.

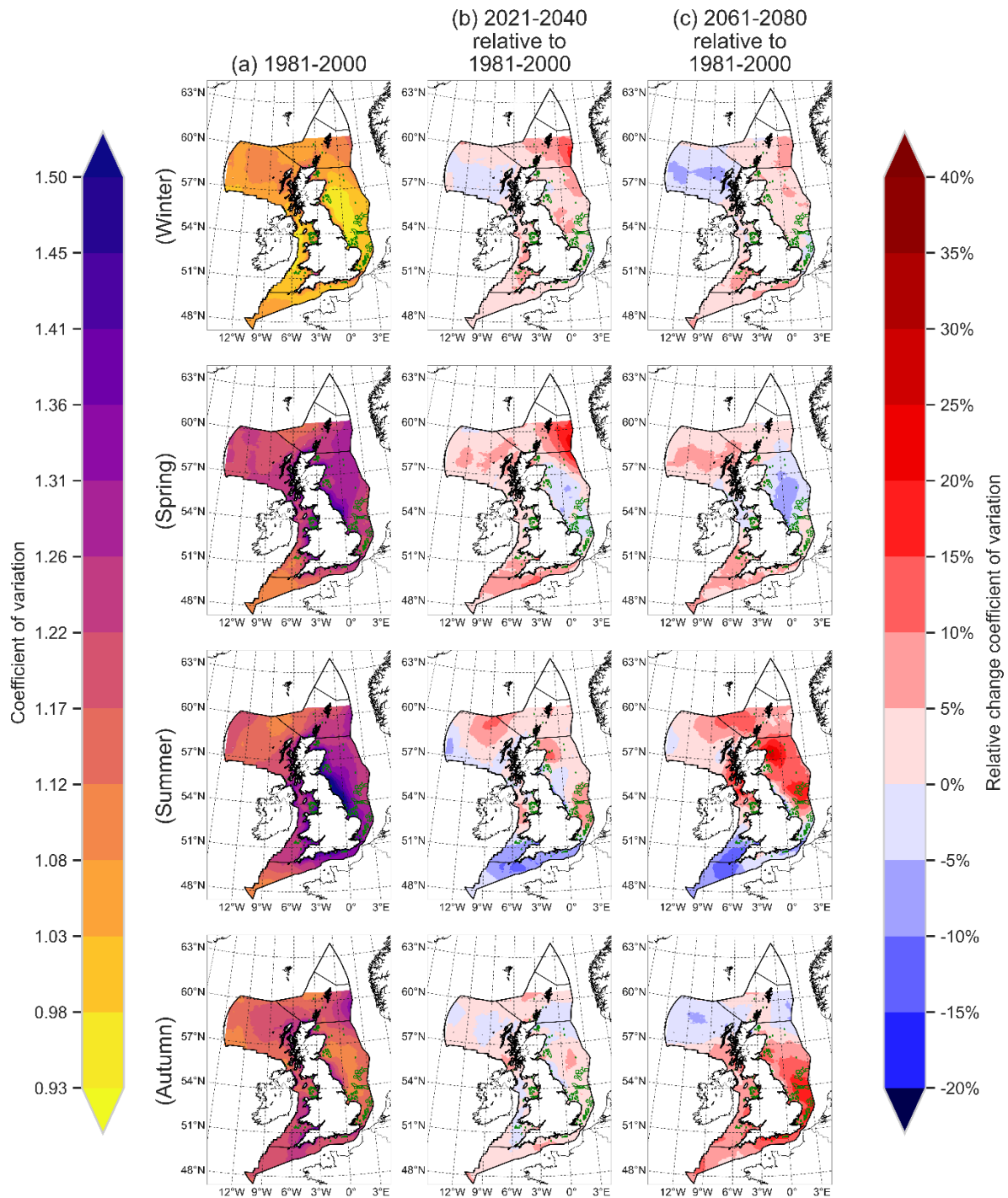


Figure 4.12. A spatial map represents the coefficient of variation calculations, rows from 1 to 4 represent the four seasons, winter, spring, summer, and autumn, respectively. Column (a) show 1981-2000, column (b) 2021-2040 relative to 1981-2000, and column (c) 2061-2080 relative to 1981-2000. Black outer boundaries represent the EEZ, and black internal boundaries represent four regions considered in the study. The green lines represent the fixed bottom wind farms and floating wind farms in UK offshore area. The data include all pre-planning, planning, construction, and operational phases.

Figure 4.13 summarises the COV calculation for each of each of the four seasons. The COV ranges are $\sim 0.5 - 2.5$. The acceptable range for COV is ≤ 1.75 , as noted in [35] and [34]. However, it is important to consider that [35] has used the 1.75 threshold for COV analysis over 24 years period (1981-2005) collectively and not on a seasonal basis, which may be the reason for choosing a high threshold such as 1.75. On the other hand, we consider the seasonal COV analysis. Different thresholds should be considered for each WPD stability index calculation due to the distinct nature of the calculations (COV is calculated for each season separately over 20 years collectively, while MV and SV are calculated for months and seasons for every year). Since the threshold was chosen to provide an intuitive understanding of the optimal value range for each parameter, in general, lower values of COV, MV, and SV are preferable, irrespective of the specific threshold used. For this analysis, we applied a threshold of 1.75 to all three factors without making any further adjustments.

The decision of the best location will be based on which has the smallest region median. Figure 4.13 indicates that the COV region median in the North region is higher in the two future periods for all seasons compared to the baseline period. Table 4.7 provides a summary of the RC outcomes in comparison to the historical period. In this context, the South region has exhibited prominent recommendations for OWFs siting during the summer in the 2021-2040 and the 2061-2080 periods.

Using the MAT threshold, the East region has the greatest difference in the winter season in the two future periods. In addition, the South region in the spring and summer seasons has the smallest region median in the two future periods, results are recorded in Table 4.8. Overall, winter is considered the most stable, as the range of COV values is less than 1.2.

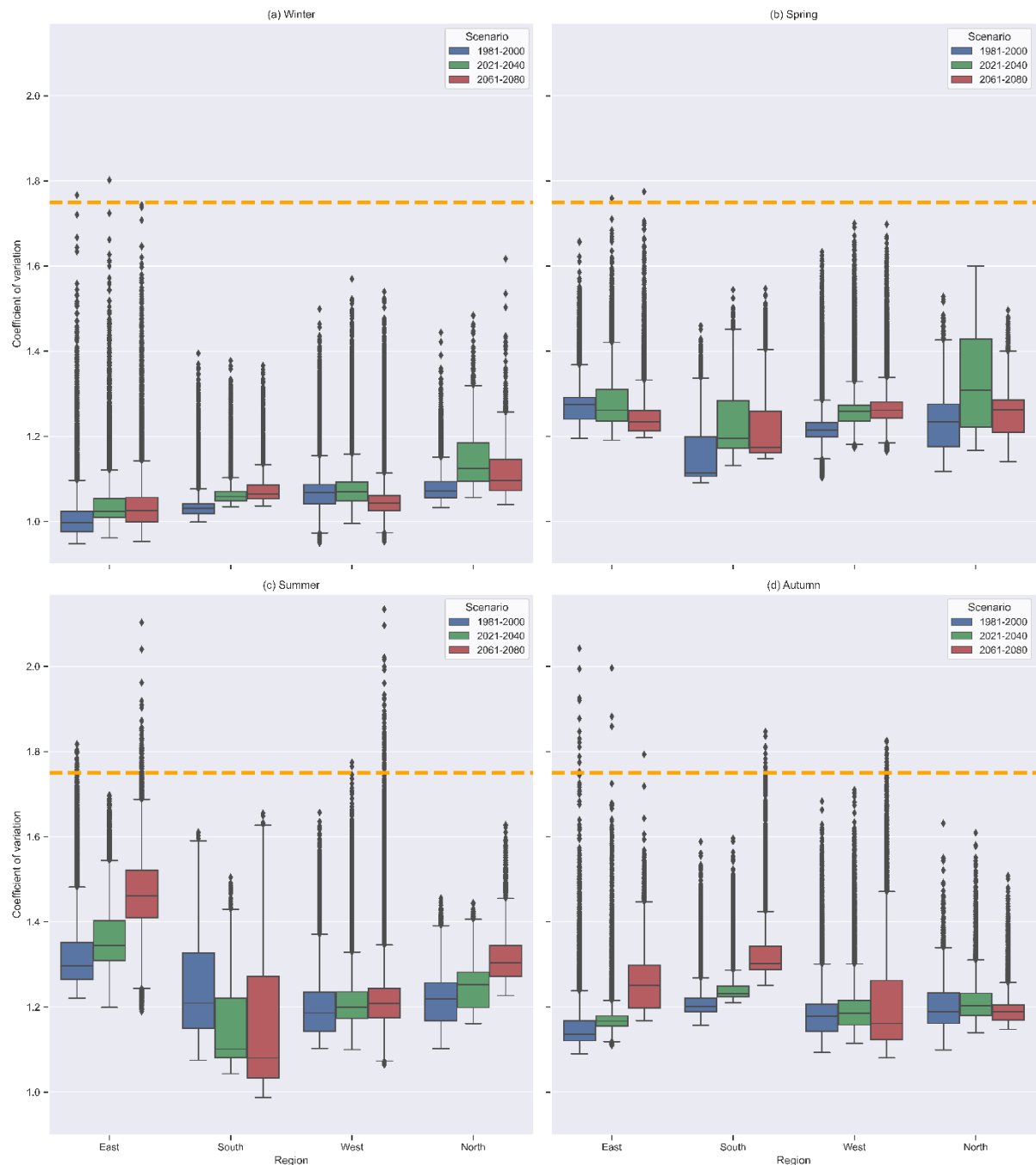


Figure 4.13. Box plot for the coefficient of variation (COV) for three periods (1981-2000 (blue), 2021-2040 (green), 2061-2080 (red)) among four seasons, (a) winter, (b) spring, (c) summer, and (d) autumn. Each plot's four comparison panels for the four regions, East, South, West, and North. The box holds the interquartile ranges (IQR), the midline represents the median. The thin vertical black line represents the rest of the distribution, except for points determined to be "outliers". The whiskers show the maximum and minimum values. The points beyond the thin vertical lines are outliers.

Table 4.7. Region recommendations for future change relative to the historical period, according to COV.

COV	Indicator	2021-2040 relative to 1981-2000				2061-2080 relative to 1981-2000			
		East	South	West	North	East	South	West	North
Winter				✓				✓✓	
Spring		✓✓				✓✓			
Summer	↓		✓✓				✓✓		
Autumn				✓				✓✓	

Table 4.8. COV region recommendations are based on the maximum absolute value.

COV	2021-2040				2061-2080			
	East	South	West	North	East	South	West	North
Winter	✓✓				✓✓			
Spring		✓✓				✓✓		
Summer		✓✓				✓✓		
Autumn	✓✓						✓✓	

✓✓: Strong recommendation, ✓: Weak recommendation, --: No recommendation, ↑: Increasing, ↓: decreasing.

4.5.4 Capacity factor (CF)

The capacity factor calculation is similar to the methodology used in [94], where the annual energy production is the expected energy, calculated as the total energy of the period for which the capacity factor is calculated. Hourly power for a complete year is calculated using equation (2.1) to determine the value of expected energy. The expected energy is the sum of the hourly power of a representative year (the sum of power for all 8760 h).

$$CF = \frac{AEP}{TC \times 8760} \quad (4.5)$$

Where CF is the capacity factor, AEP is the annual energy production, TC is the turbine capacity = 17 MW [12], the number of hours in each year = 8760 hr, and $AEP = \sum_{i=1}^{i=n} P_i$, n : the number of hours in a year and P_i is the wind turbine's actual power output [95] calculated spatially using hourly mean wind speed.

In Figure 4.14 (a), the CF calculations indicate that most values are within the desired range of 50% to 70%. In [96], annual capacity factor output can reach 60% in high wind areas. The use

of the 17 MW wind turbine model has led to an improvement in power output. Figure 4.14 (b) shows the RC for the 2021-2040 period to the 1981-2000 period, revealing a decrease of up to 4% in CF using a 17 MW wind turbine everywhere, except for locations near latitude 51° N specifically, the northwest of Lundy area near the coast in the West region. Figure 4.14 (c) demonstrates that the Tyne, Forth, Cromarty, Dogger, and Humber regions have a lower CF in the 2061-2080 period compared to the 1981-2000 period of around 6%. Moreover, the statistical summary of the CF in Figure 4.15 reveals a consistent drop in the regional median in the two future periods compared to the baseline period. Accordingly, when using the 17MW wind turbine no region can be strongly recommended compared to the historical period, see Table 4.9. The MAT of 20% was selected, as discussed before in section 4.4.2, for the CF calculations. However, for both the 2021-2040 and 2061-2080 periods, it was found that the West region has the greatest difference between its median and the 20% threshold, as recorded in Table 4.9.

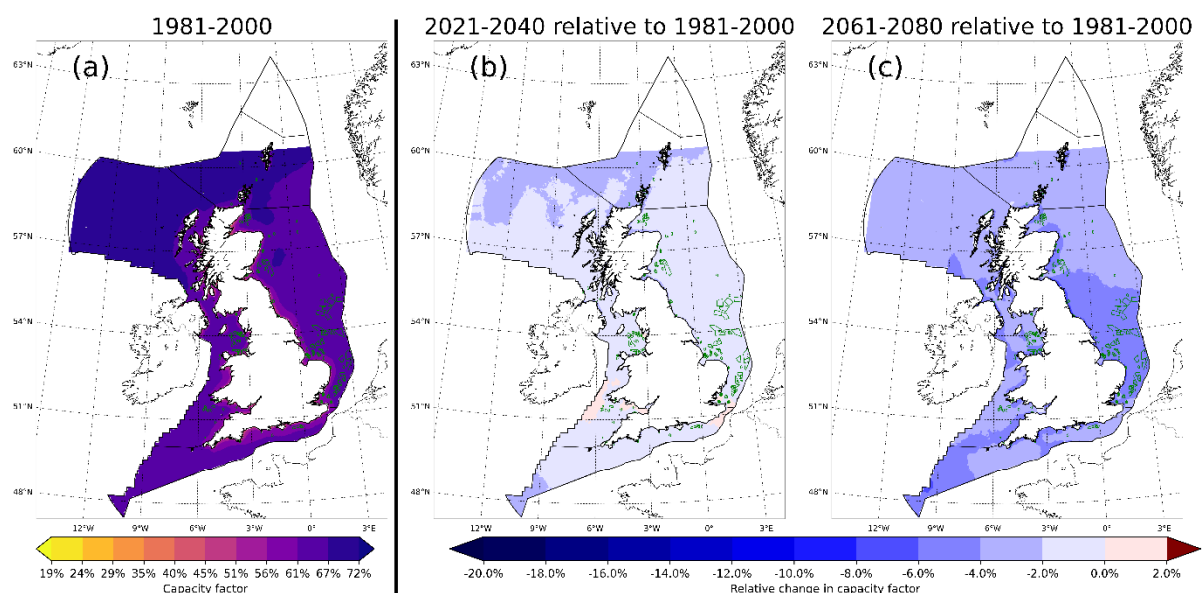


Figure 4.14. The hourly mean capacity factor (CF) for 20 years hourly mean wind speed. The three figures represent the climate periods (a) 1981-2000, (b) 2021-2040 relative to 1981-2000, and (c) 2061-2080 relative to 1981-2000. Black outer boundaries represent the EEZ, and black internal boundaries represent four regions considered in the study. The green lines represent the UK fixed bottom wind farms and floating wind farms in UK offshore area. The data include all pre-planning, planning, construction, and operational phases.

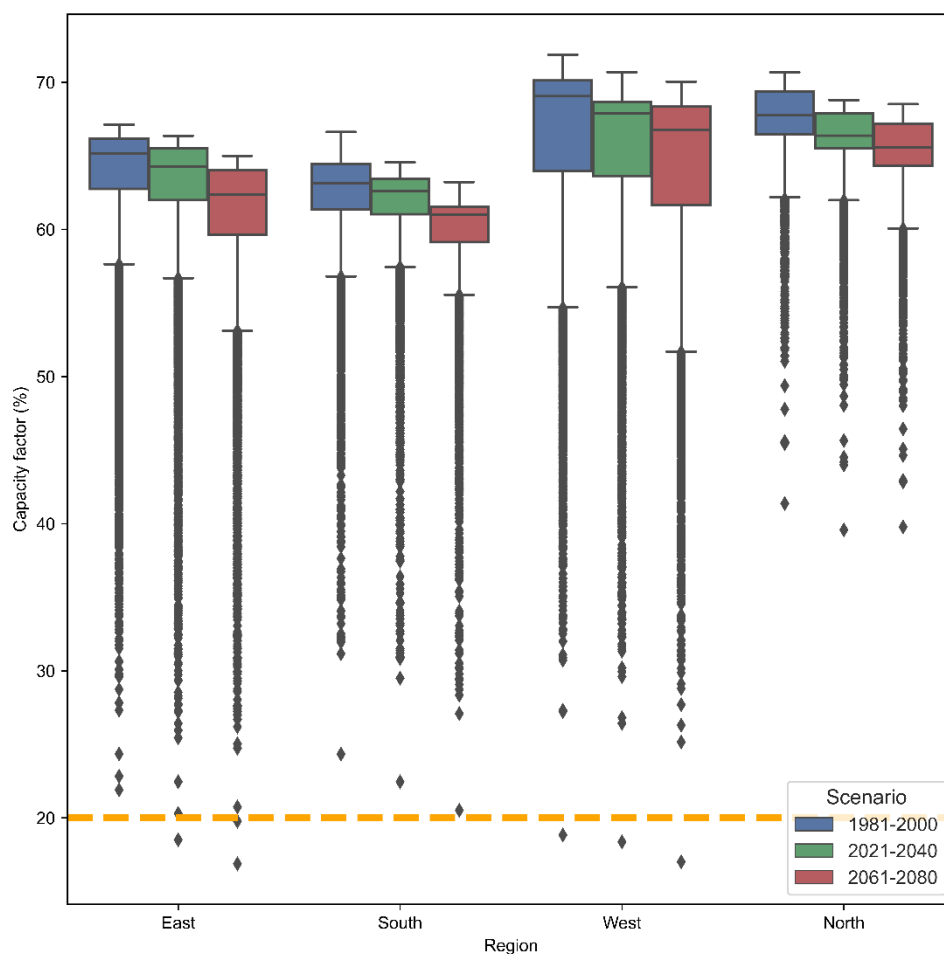


Figure 4.15. Box plot for capacity factor (CF) for three climate periods 1981-2000 (blue), 2021-2040 (green), and 2061-2080 (red). The x-axis compares the four regions (East, South, West, and North). The horizontal orange line indicates the 20% minimum acceptable threshold (MAT). The box holds the interquartile ranges (IQR), and the midline represents the median. The thin vertical black line represents the rest of the distribution, except for points determined to be “outliers”. The whiskers show the maximum and minimum values. The points beyond the thin vertical lines are outliers.

Table 4.9. Region’s recommendations for capacity factor (CF) future change relative to the historical period in first row and the maximum absolute value is in the second row.

Factor	Indicator	2021-2040 relative to 1981-2000				2061-2080 relative to 1981-2000			
		East	South	West	North	East	South	West	North
Capacity factor	↑	--	--	--	--	--	--	--	--
		2021-2040				2061-2080			
Capacity factor		✓✓				✓✓			

✓✓: Strong recommendation, ✓: Weak recommendation, --: No recommendation, ↑: Increasing, ↓: decreasing.

Figure 4.16 displays a comparison of the 20 years of hourly CF between the baseline period and two future periods using box plots. Although most CF high probability values are above 50%, 50% of the years in the two future periods had a lower CF median value compared to the baseline period.

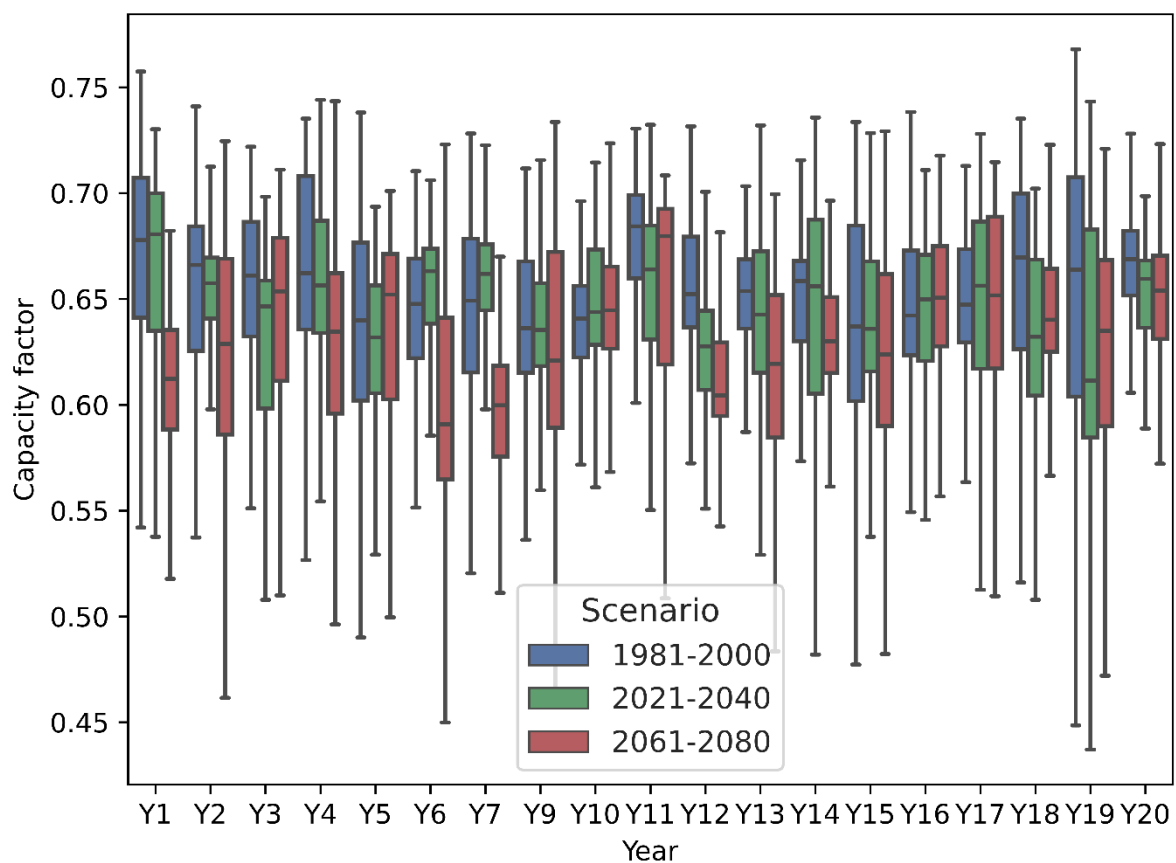


Figure 4.16. Twenty years capacity factor (CF) using hourly mean wind speed. 1981-2000 (blue), 2021-2040 (green), and 2061-2080 (red). The middle horizontal line represents the median.

The 17 MW turbine was chosen because it aligns with the industry trend of increasing turbine sizes for offshore wind farms, which can capture more wind energy and offer higher capacity factors. This trend is particularly important in regions with higher average wind speeds, such as the North Sea, where larger turbines are becoming the norm for new installations. The

assumption of larger turbines, such as the 17 MW model, naturally leads to higher capacity factor estimates due to the higher-rated power and improved performance in stronger wind conditions. This is consistent with the expected evolution of the wind energy industry, particularly in offshore installations. For comparison, the capacity factor for a smaller turbine model V117-3.3 MW [97] was also calculated and presented in Figure 4.17. This demonstrates that smaller turbines, which are less common in new installations, yield lower capacity factors, reflecting the limitations of their rated power in capturing available wind energy. However, the key focus of this study remains on larger turbines, which are more relevant to the future of offshore wind energy development. The findings related to capacity factor and wind power production in this study are specific to the 17 MW turbine considered, which is representative of the larger turbines being deployed in the offshore wind industry. While smaller turbines were also analysed for comparison in Figure 4.17, the results are more relevant to future developments that will likely favour larger turbines with higher capacity factors.

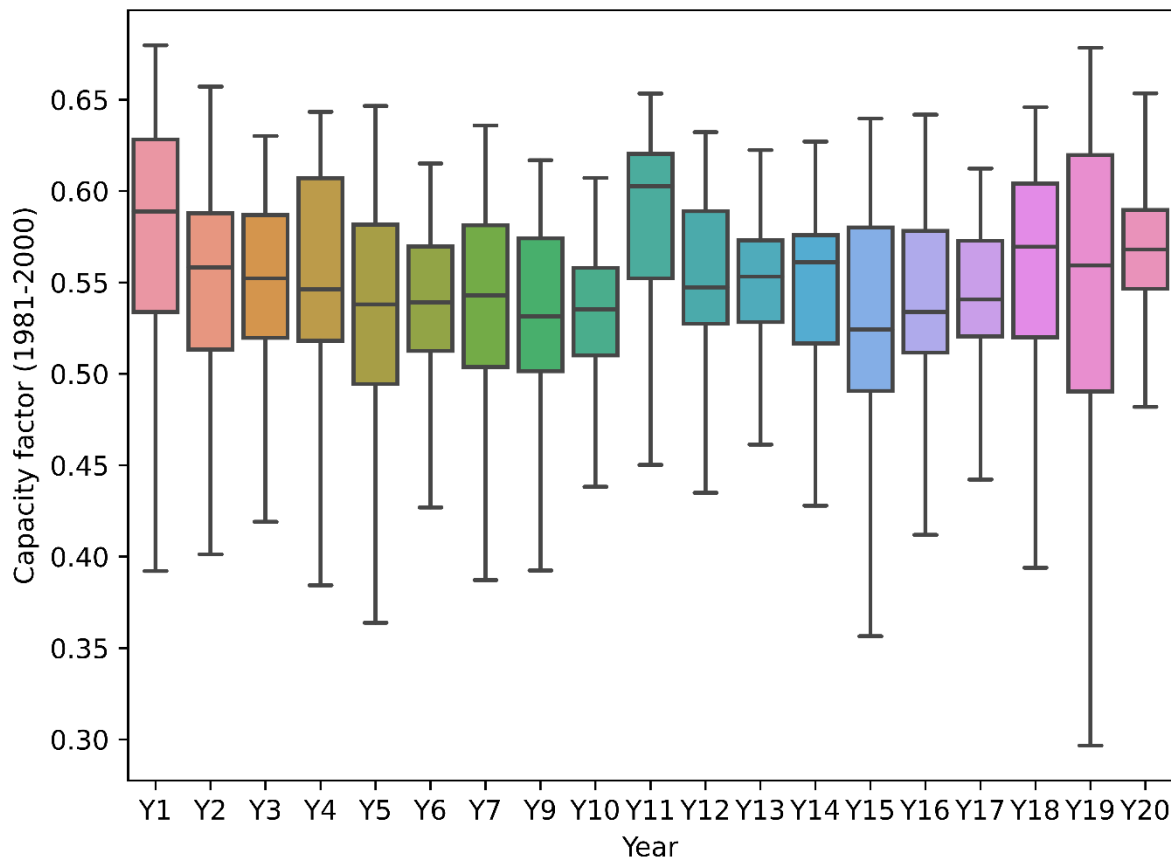


Figure 4.17. Twenty years capacity factor (CF) using hourly mean wind speed (1981-2000). The wind turbine model used is V117-3.3 MW. The middle horizontal line represents the median.

4.6 Wind energy production conclusion remarks

This chapter analysed the long-term wind production and stability in the UK EEZ for the historical period and two future periods. This is crucial as it has a remarkable long-run economic impact and can impact decisions made by policymakers and wind generation companies regarding the expansion and installation of OWFs. This chapter results in two key analyses, RC to the historical period and change between region median to MAT. For RC to historical period calculations: the favourable locations indicate that current OWF (in the region selected as favourable) are experiencing a positive impact of climate change. On the other hand, the MAT analysis gives a comprehensive view when comparing regions. As one region can

have the majority of its locations experiencing unfavourable impacts from climate change in the future, at the same time, its median value has a significant change to MAT. For example, in Figure 4.15, the West region has a significant decrease in CF for the two future periods compared to the baseline period (results are recorded in Table 4.9). At the same time, the region median in the two future periods has the highest CF values compared to other regions (also the largest difference to MAT) (results are recorded in Table 4.9). Moreover, although the South region has a region median closest to 20% MAT compared to other regions, most sites in the region have high future generation capacity in the 60% to 65% range, which is considered suitable for wind power generation. It depends on the policymaker whether the priority is to repower the current installed OWF because of geophysical constraints or to consider installing OWF in new locations to achieve better wind generation.

The chapter results showed that:

- The seasonal production evaluation revealed one to two class drop-in WPD classes during summer in the two future periods. However, the summer season was found to have high stability in WPD. Moreover, the autumn season showed the same classes drop below latitude 55° N in the 2061-2080 period.
- The future changes in the CF calculated collectively for 20 years are projected to decrease consistently in all regions, which suggests an increased risk of lower energy production using the 17 MW wind turbine assumption.
- The yearly CF calculations indicate that the historical and future periods for offshore regions surrounding the UK have a CF IQR of ~ 56% to 71% and the variation of the median CF (0.6 to 0.68). The presence of abundant wind energy resources suggests the UK's EEZ holds great potential for wind energy production. On the other hand, 50% of the 20 years have a lower CF median in the two future periods than the baseline period.

- The comparison of the 2021-2040 period to the 1981-2000 period shows a reduction of up to 4% in CF for a 17 MW wind turbine across most locations, except areas near latitude 51° N. Looking further ahead, the Tyne, Forth, Cromarty, Dogger, and Humber regions are expected to experience an even decline in CF, with a decrease of around 6% for the 2061-2080 period relative to 1981-2000. This highlights the reduction in wind energy potential in these areas over time.
- The West and South regions have been identified as the most resilient areas with respect to future climate change based on the majority of factors considered. These regions are thus highly recommended, as demonstrated by the difference observed between the median of the regions and the MAT in both future periods. However, using COV analysis, the East region is recommended for the winter season for two future periods and autumn for the first future period.
- Currently, most existing wind farm installations are located in the East region. However, based on the MAT analysis, the East region has not been included in most recommendations for future OWF expansion. Hence, future policies for OWF expansion in the UK must be carefully crafted, considering future wind energy production changes in the UK offshore areas.

Chapter 5 Assessing long-term future climate change impacts on extreme low wind speed events

5.1 Overview

To ensure the dependability and affordability of wind energy, it is necessary to address extreme low wind speed events (LWE). This chapter aims to assess the reliability of wind power in the future by analysing the rise of low wind durations and intensities in 2021-2040 and 2061-2080 periods, compared to the historical period. The study compares the results for four main regions in the UK EEZ: East, South, West, and North. The different cut-in thresholds of 3 m/s, 4 m/s, 5 m/s, and 6 m/s in the UK EEZ have been examined [98]–[101], [102]. The work described within this chapter was published in the Journal of Applied Energy (**Abdelaziz et al. 2023b** from Related Publication section)

5.2 Introduction

Less research has investigated the persistence of extremely low LWE and their variability. However, still weather has noticeably affected wind generation [103]. For instance, Scottish and Southern Electricity, a UK-based power company, said that its renewable assets produced 32% less power than expected in the period from 1 April 2021 to 22 September 2021, and an 11% decrease in forecast total output for the full year [103]. Also, the latest IPCC report suggests that average wind speeds over the European region will reduce by 8%-10% as a result of future climate change [104]–[106].

Extreme weather events are expected to occur more often due to climate change; they must be accounted for with an in-depth assessment of their duration and severity during the spatial planning of future OWF. Estimating extreme wind speeds is a critical component of wind turbine design for capital costs, structural integrity, and site selection [13]. Investigating the persistence of LWE is centred on two methods. The first uses a CF threshold below which a count is made of consecutive days [107]–[110].

The second method uses one or more cut-in wind speed thresholds to investigate LWE. Here, we focus on literature that tackles the second method for investigating LWE, as this study mainly focuses on utilising a cut-in wind speed threshold to identify extreme LWE. In 2017, Patlakas et al. [98] used 10 years of the MARINA database to investigate LWE in five North Sea locations, using a wind speed threshold of 3 m/s to identify low wind durations and found that most events have a 4 to 5 day duration in open sea areas. In Leahy and McKeogh [99], durations of 1 hour to 20 days were investigated for LWE in Ireland. The research used a running mean to match each of the durations selected in the study, and the annual minimum was used following Khaliq et al. [100] approach that calculates heatwave duration and frequencies from daily maximum temperature records. The probability of remaining below thresholds of 4 m/s, 6 m/s, and 10 m/s was investigated, and it was shown that sustained LWE lasting 20 days have return periods (using a Gumbel distribution) of around ten years for near-shore areas. Using ERA-Interim Reanalysis, Weber et al. [101] calculated the durations of persistent LWE under the 4 m/s threshold. The durations are used to investigate wind persistence statistically. The research found that q -exponential distributions had a good performance fitting the duration data all over Europe.

We have concluded from the existing literature that, although LWEs are rare, they can last for several days. Moreover, using more than one distribution to assess the data best fit is highly recommended, especially for studies considering extreme weather events (which focus

on heavy tails). Investigating climate change signals can ensure a reliable and economically feasible future energy system. Analysing durations and magnitude of LWE are desired to construct a comprehensive understanding of LWE risk in current and future warming periods and optimise locations for future wind resource development.

This chapter focuses on LWE that occurs below cut-in wind speed values and in the mean of the distribution in the UK Exclusive Economic Zone (EEZ). The main key contributions of this chapter are:

- Quantifying the seasonal change in low wind speed in the mean of the distribution and the future change in the 8th percentile of wind speed for all locations in the UK EEZ.
- Examining the frequency and duration of low wind speeds seasonally in the two future periods.
- Investigating the likelihood of different LWE magnitudes using multiple time windows.

The chapter is organised as follows: In section 5.3 the four methods of low wind speed analysis are described, including investigating the seasonal variation of daily mean wind speed and 8th percentile of wind speed, analysing the future changes in low wind speed duration, and illustrating the return periods for LWE magnitudes of 4 m/s, 5 m/s, and 6 m/s using a 5 day running mean and the return periods for a 4 m/s LWE using running means of 7, 8, and 8 days. Sections 5.4 and 5.5 provide the discussion and the conclusion for this chapter findings.

5.3 Future change in low wind speed.

The understanding of the future change of low wind speed was built on four principal analyses used to investigate different meteorological aspects of wind speed. The next four sub-sections illustrate these aspects. The first aspect is the future change in the entire distribution of the mean wind speed, where the change in the mean of the distribution can be detected,

corresponding to the range of wind speed associated with energy production. The second aspect is to investigate the instantaneous change in wind speed in the future under a certain percentile, which shows us the amount of change in the left tail of the distribution in the two future periods compared to historical periods. The third aspect is focused on investigating the duration of low wind speed under multiple cut-in wind speed thresholds. The fourth aspect investigates the probability of future reoccurrences of multiple LWE definitions using different time windows and wind speed thresholds.

5.3.1 Change in daily mean wind speed distribution.

To investigate the impact of the warming scenario on future wind production, we use the cumulative distribution function (CDF) to analyse future changes in wind speed distribution. Figure 5.1 presents the future wind speed distribution in the UK EEZ through the CDF and future wind speed distribution in four regions of the UK. All analysis is based on the daily mean wind speed dataset. In Figure 5.1, the summer and autumn seasons in all regions exhibit a shift toward lower wind speeds in one or two of the future periods compared to the baseline period. On the other hand, in the summer, for wind speed < 5 m/s in the South region, there is no change in the 2061-2080 periods compared to the historical period and a slight decrease of low wind in 2021-2040 compared to the historical period. Moreover, in the autumn, there is no decrease in wind speed for the 2021-2040 period compared to the historical period in the South and West regions. In the winter, the West and North regions witness a notable decrease in wind speed compared to the historical period in the 2021-2040 period. In the spring, the empirical CDF for these two regions shows no decrease in wind speed in the 2021-2040.

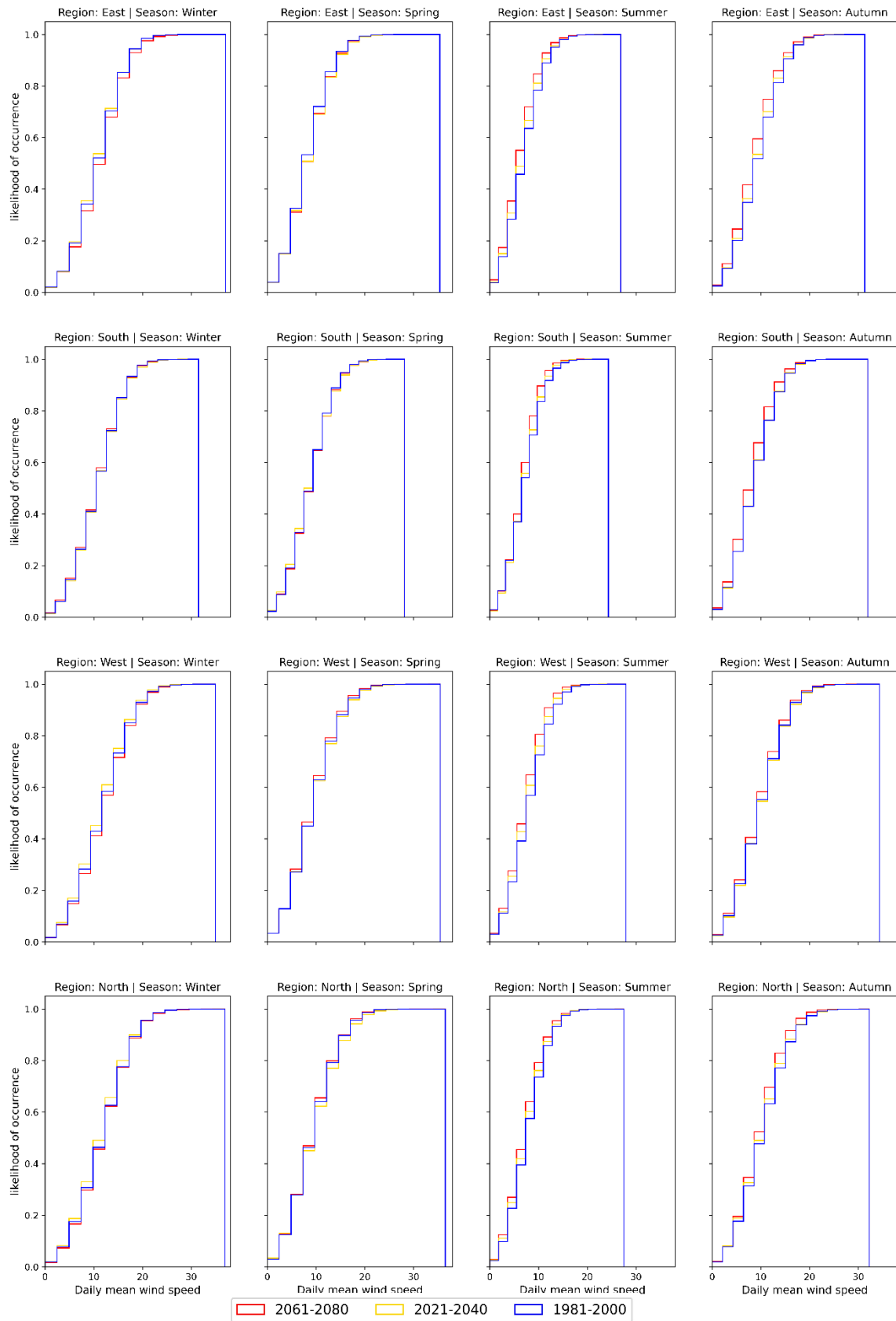


Figure 5.1. Cumulative distribution function plots of daily mean wind speed. Blue, yellow, and red represent the 1981-2000, 2021-2040, and 2061-2080 periods, respectively. Rows represent the four regions: East, South, West, and North. Columns represent the four seasons from left to right: winter, spring, summer, and autumn.

5.3.2 8th percentile daily mean wind speed

Energy generation by wind turbines requires wind speeds within a specific range, defined by the cut-in value (minimum wind speed) and cut-off value (maximum wind speed) [26], see Figure 2.2. When wind speeds are too low, the torque generated by the air is insufficient to rotate the wind turbine blades, resulting in the inability to produce energy. The wind speed at which the wind turbine blades start to spin and convert mechanical energy into electrical energy is known as the cut-in wind speed, typically ranging from 3 m/s to 6 m/s [98]–[101], [102]. This section examines the future changes in low wind speeds at the 5th, 6th, 7th, 8th, and 10th percentile to determine at which percentile we have a range of wind speed across all seasons that cover the most common values of cut-in wind speed (<6 m/s). By defining the percentile that best matches the most common range of cut-in wind speed thresholds across the four seasons, we will be able to estimate the change in the two future periods by applying the percentile value on the three climate periods and quantify the change in the corresponding wind speed for the two future periods compared to the historical period.

We found that the 8th percentile best represents the cut-in wind speed of less than 6 m/s across all seasons, which will be discussed in this section. Maps for the future changes in the 5th, 6th, 7th, and 10th percentile can be found in **Appendix A**. Maps showing the 8th percentile for each season are depicted in Figure 5.2 (a), (d), (g), and (j) using the 1981-2000 period. During the winter, the highest range of low wind speed is observed, with majority of locations averaging between 4.0 to 6.0 m/s. Conversely, the lowest values for the 8th percentile are recorded in the summer, ranging from 1.0 to 4.0 m/s. The 8th percentile wind speed is lowest near coastline areas compared to open sea areas across the four seasons. In columns 2 and 3, the relative change for the two future periods is calculated using equation (4.2) from chapter 4 section 4.4.1.

A negative relative change percentage (blue shades in Figure 5.2, column 2 and 3) indicates a shift toward a smaller wind speed value in the left tail of the wind speed distribution in the location, indicating a prone location for extremely low wind speed in the future. In Figure 5.2, the summer season experienced the largest decrease in the 8th percentile with a range from 5% to 25% in the 2021-2040 period compared to the 1981-2000 period in the East, West, and North regions. Meanwhile, the north-west of the UK experiences a decrease in wind speed in the winter season from 5% to 15%. The 2061-2080 period also shows a reduction in wind speed in locations above latitude 51° N during the summer.

Figure 5.3 shows the statistical representation of Figure 5.2, where the region median, the 25 quantiles, and the 75 quantiles are calculated for each region in the four seasons. Figure 5.3 shows that the median low wind speed in the future will decrease in the East, West, and North regions during the summer, while the South region has the lowest risk of reducing wind speed. The autumn season in the 2061-2080 period has a lower median of 3.6 m/s compared to 4.0 m/s in the baseline period for the East region. During the winter season, the 2021-2040 period shows a decreasing median in the West and North regions compared to the baseline period.

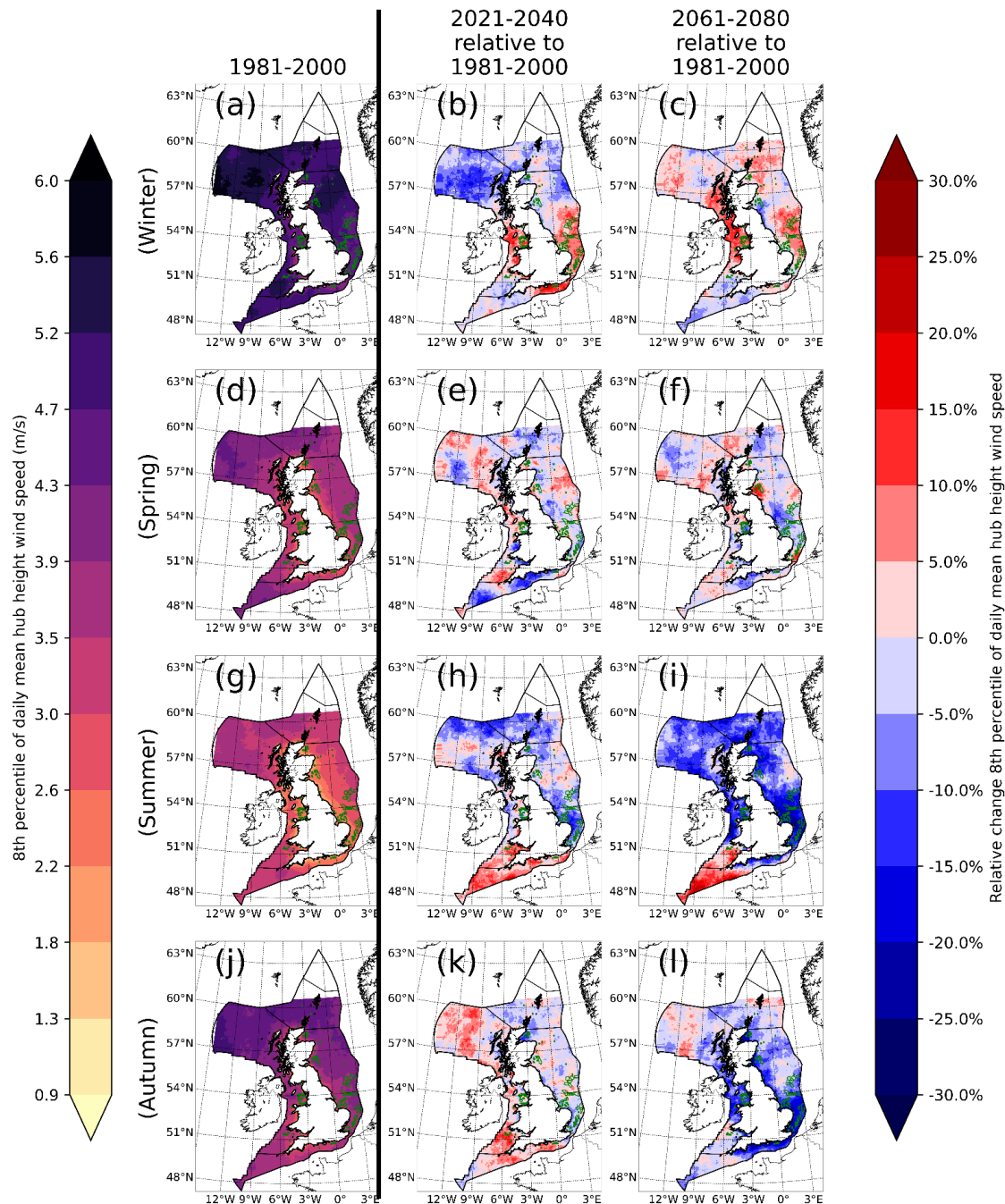


Figure 5.2. Column 1 from left side: 8th percentile of daily mean hub height wind speed in the four seasons for the 1981-2000 period. Rows from 1 to 4 represent the four seasons: winter, spring, summer, and autumn. Column 2 and 3 from the left side: shows the relative change of 2021-2040 and 2061-2080 to 1981-2000, respectively. The green lines represent the fixed bottom wind farms and floating wind farms in UK offshore area. The data include all pre-planning, planning, construction, and operational phases.

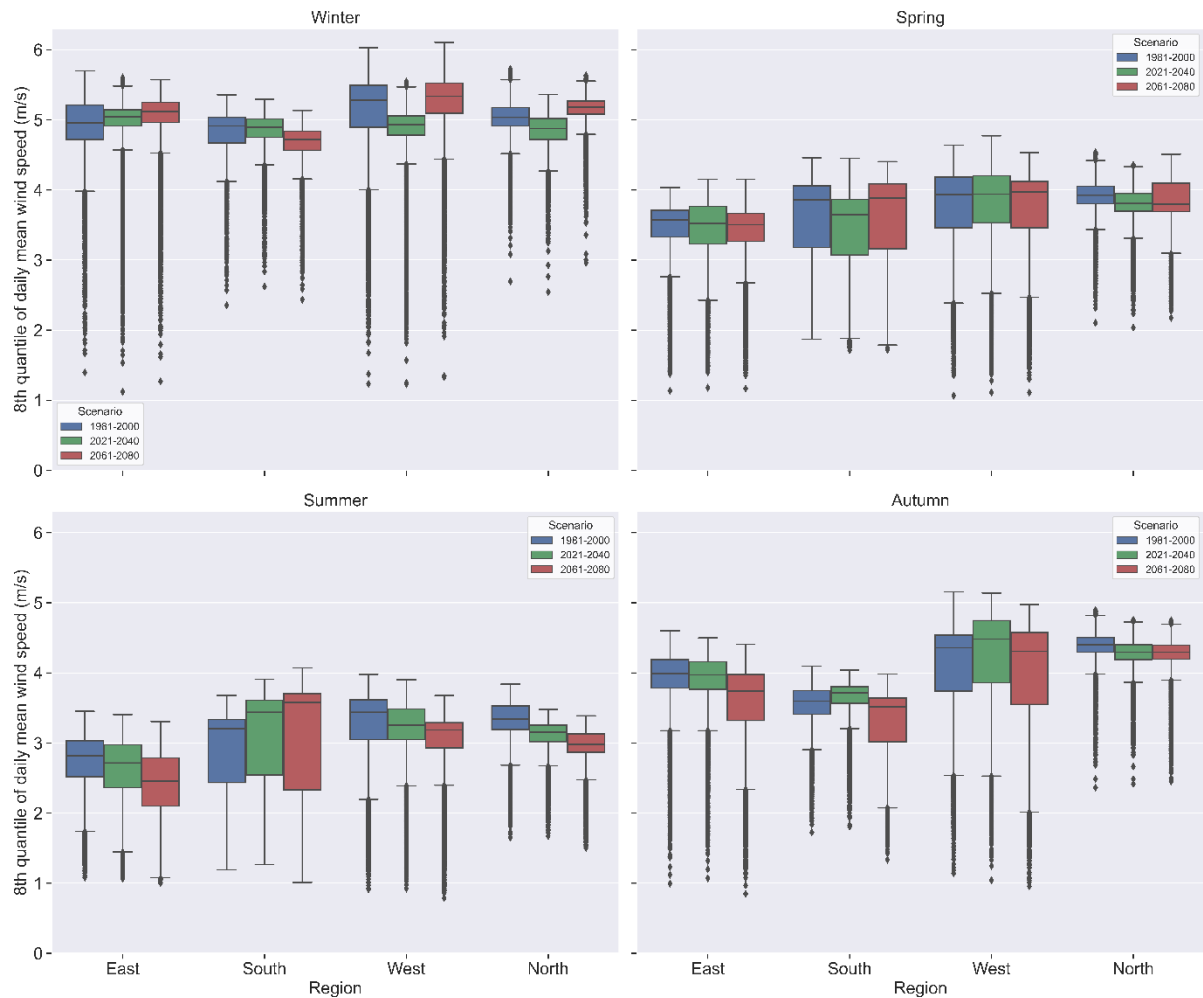


Figure 5.3. Box plot to compare the 8th percentile of daily mean wind speed for three periods (1981-2000 (blue), 2021-2040 (green), 2061-2080 (red)) among four seasons (winter, spring, summer, and autumn). In each plot, the four panels of comparison are the four regions, East, South, West, and North. The box holds the interquartile ranges (IQR), and the midline represents the median. The whiskers show the maximum and minimum values. The thin vertical black line represents the rest of the distribution, except for points determined to be “outliers”.

5.3.3 Duration of low wind speed events under 3 m/s, 4 m/s, 5 m/s, and 6 m/s thresholds.

Low generation by renewables for an extended period of time, such as several days, can put pressure on the electricity system, particularly during high demand periods [111]. The persistence of LWE can be determined similarly to the calculation of water drought events, both of which are measured by counting the consecutive hours, days, or months that fall below a certain threshold [101], [112], [113]. The standardised precipitation index (SPI) is widely used as a threshold in water drought analysis, but it is also important to note that various indices

have been utilised [113]. In this study, we have established thresholds specific to the wind energy industry and represent a safe level of wind turbine power generation. Figure 5.4 shows how the LWE is calculated by counting the entire period (in red) when the daily average wind speed drops below the cut-in wind speed threshold (black horizontal line) until it rises above the threshold again. The consecutive days under this threshold are recorded as LWE for historical data and two future periods.

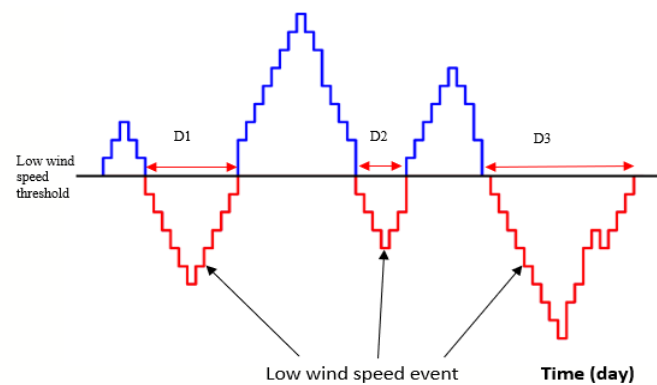


Figure 5.4. The schematic diagram for LWE durations. The black horizontal line is the cut-in wind speed thresholds used in this research (3 m/s, 4 m/s, 5 m/s, and 6 m/s). The red line represents the periods of LWE under the threshold. The blue line represents the periods over the threshold, so they are not calculated for LWE. D1, D2, and D3 are the durations calculated from the number of days that occurred under a certain threshold.

Figure 5.5 shows the maximum repetition of LWE for durations greater than 5 days, with cut-in speeds of 3 m/s, 4 m/s, 5 m/s, and 6 m/s, computed for each cell grid from historical data and two potential future periods. The durations that surpass five continuous days are taken into consideration, as they are considered the starting point of potential stress on electricity generation [107]. A noticeable variation is evident between the durations under different speed limits, with the most notable occurrence of low wind speed durations happening at the higher cut-in wind speed thresholds. Additionally, as expected, the repetition of durations under higher cut-in thresholds is more pronounced than lower ones. A common pattern among all durations under all thresholds is the high repetition frequency for events with short durations, as opposed to others with longer durations. It is also worth noting that the baseline and future periods under

any threshold have higher repetition values than those under lower thresholds. The maximum number of consecutive days observed under 3 m/s, 4 m/s, 5 m/s, and 6 m/s are approximately 20, 30, 40, and 50 days, respectively. As seen, there is a difference of ten consecutive days between the maximum durations recorded for the four cut-in thresholds.

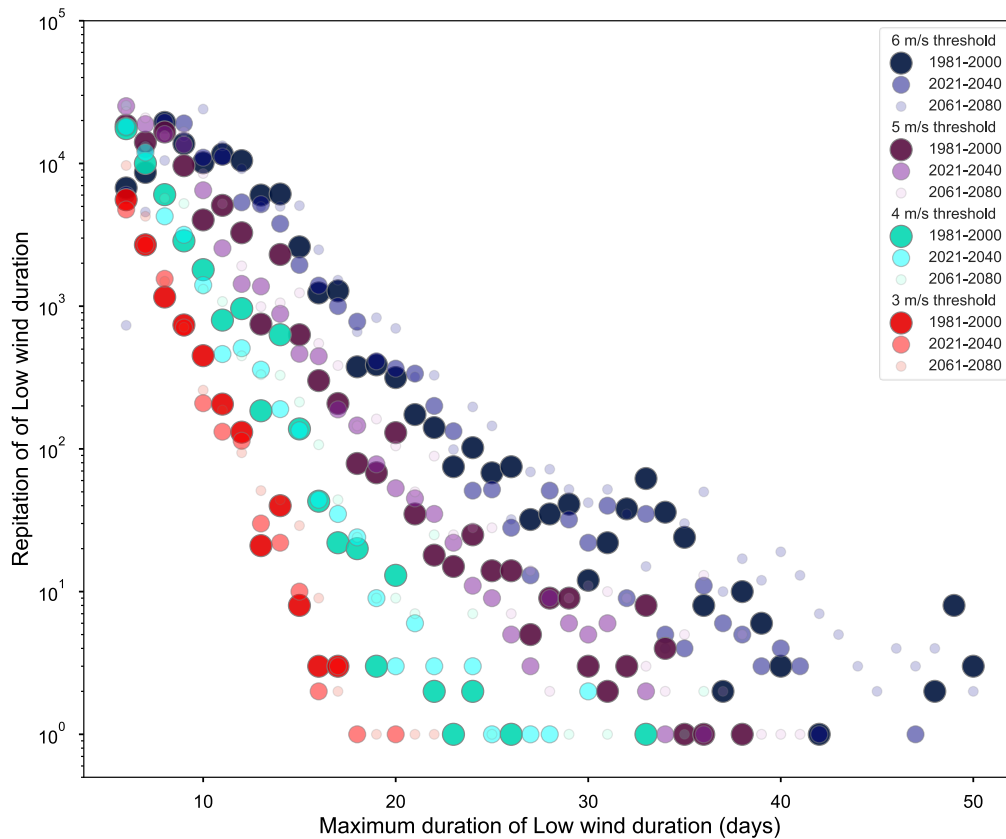


Figure 5.5. Scatter diagram for the maximum low wind speed durations occurred in each cell grid calculated for 20 years under 6 m/s, 5 m/s, 4 m/s, and 3 m/s. Only durations $\geq$ five consecutive days are shown.

Durations lasting 15 or more consecutive days are found near the UK coastline. Figure 5.6 presents LWE lasting 15 or more consecutive days for the 3 m/s, 4 m/s, 5 m/s, and 6 m/s thresholds using the 1981-2000 period. The longest durations under each threshold are all situated close to the UK coastline, which confirms findings from Patlakas et al. [98] that there were 20 consecutive days of low wind speed over ten years near the UK coastline in the North Sea. As stated by Patlakas et al. [98], the main reason for these extremely high durations near-shore areas could be the interaction of complex terrain with the atmosphere and its

representation within the climate model configuration. Additionally, the flow in areas with complex altitudes, such as coastlines, is challenging due to dynamic and thermodynamic effects, such as channelling, sea-land barriers, and boundary layers.

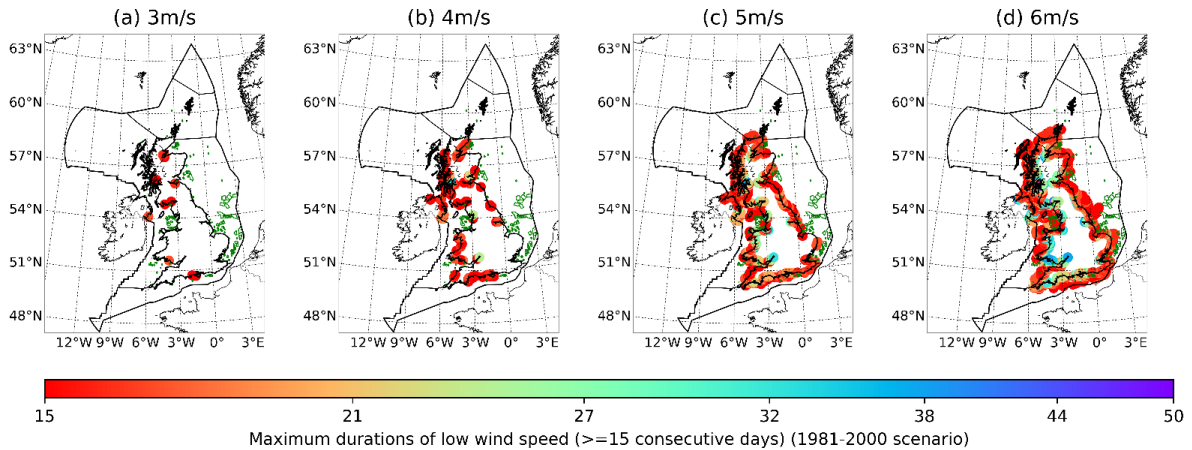


Figure 5.6. ≥ 15 consecutive days of low wind durations in the 1981-2020 period. The count of consecutive days has been done for three thresholds: (a) 3 m/s, (b) 4 m/s, (c) 5 m/s, and (d) 6 m/s.

Following Patlakas et al. [98] suggestion that extremely long durations occurring on coastline locations could be a result of the model configuration, we will remove durations ≥ 15 days in the investigation of the seasonal variation in low wind speed duration in Figure 5.7. The variability in the prolonged periods of low wind speed across seasons in two future periods compared to the baseline period is analysed in Figure 5.7. In Figure 5.7, the histogram depicts durations lasting between five consecutive days and 15 consecutive days in each cell grid for a 4 m/s threshold, and it is a representation of the maximum duration calculated in each cell grid in the EEZ, where we found that durations lasting less than 15 days are more concentrated near the coastline and decrease gradually toward the open sea locations.

A logarithmic scale represents the frequency of events because of the high frequency of low durations (especially five consecutive days) and the low frequency of high durations (rare LWE). The North region has the smallest range of durations in the spring season, around

5 to 10 days, while the West region has the highest range throughout all seasons for the three time periods, from 5 to 15 days. In most regions and seasons, one or two of the future periods have more occurrences of longer duration of LWE compared to the baseline period. For example, the South region has increased LWE durations in one or two future periods in all seasons. On the other hand, in the West region, the occurrence of low wind speed duration in the two future periods has a marginal increase compared to the historical period in the spring. In general, the maximum duration values are greater in the summer and autumn seasons in all four regions than in the winter and spring seasons.

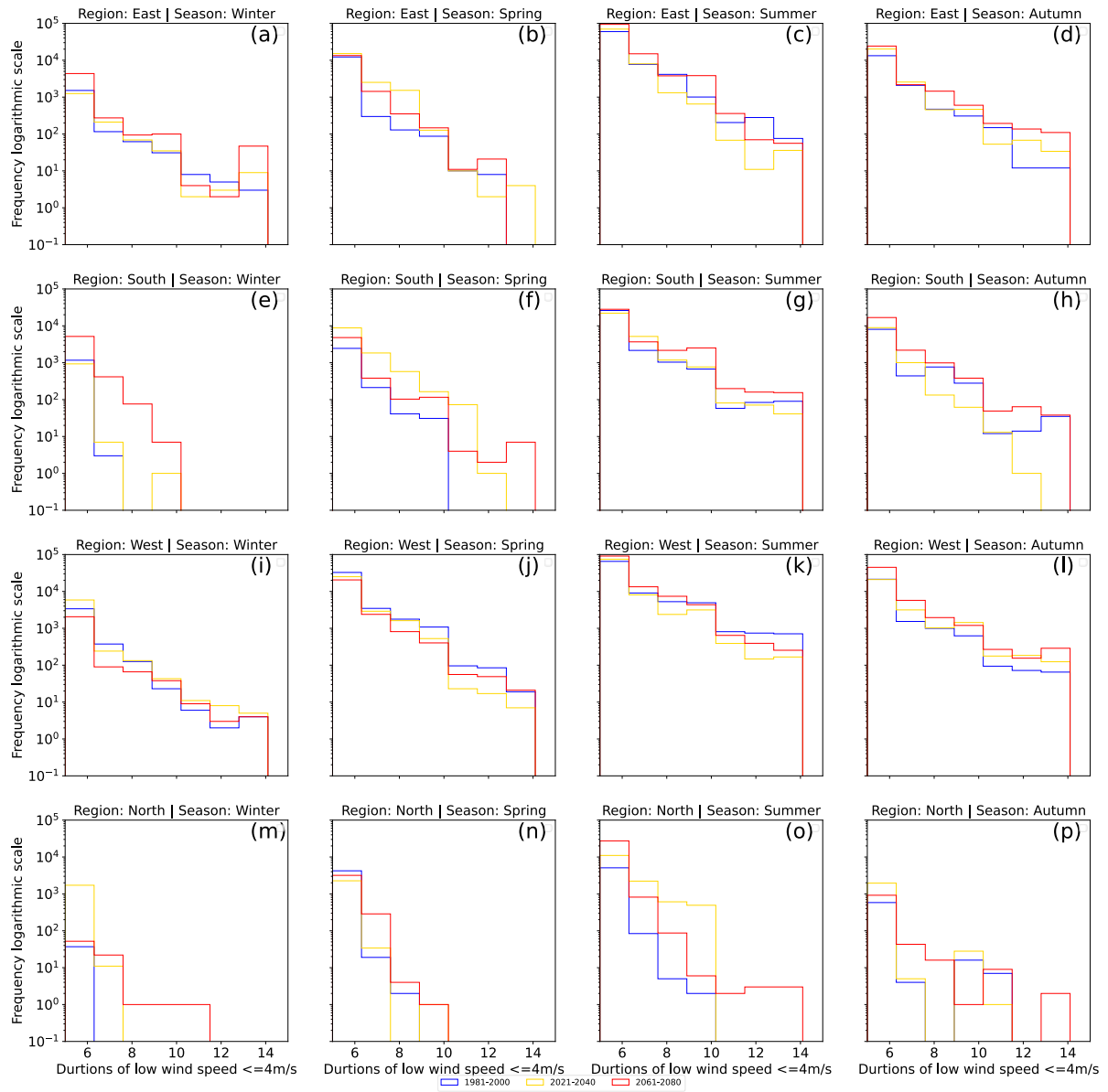


Figure 5.7. Histogram of low wind speed durations less than 4 m/s. Blue, yellow, and red represent the 1981-2000, 2021-2040, and 2061-2080 periods, respectively. The four rows represent the regions: East, South, West, and North (from top to bottom).

5.3.4 Return period for low wind speed event magnitude pre-processing.

The return frequency of LWE can be calculated using the same method as for water droughts [114]. The probability of recurrence below the cut-in threshold is used to determine the corresponding return period. In 1981-2000, three distributions were used to predict the best fit for the 5, 6, 7, and 8 day running mean data statistics at a hub height of 151 m for each grid

cell in the UK EEZ. These distributions include Generalised Extreme Value (GEV) [115], Exponential Weibull [116], and Beta [117].

MAE, RMSE, and Kolmogorov-Smirnov (K-S) tests were used to evaluate the best-fit distribution for the data [118]. The K-S test uses the P-value to determine the statistical significance of the observed difference, and the alpha value 0.01 represents a 99% confidence level. Table 5.1 presents the results of the P-values, MAE, and RMSE for the 5, 6, 7, and 8 day running mean data. The results show that the Beta distribution produces the highest percentage of cell grid with a P-value greater than 0.01, equal to 99.9% for the 5 and 6 day running mean data and 99.5% and 96% for the 7 and 8-day running mean data, respectively. Additionally, the Beta distribution has the lowest values for MAE and RMSE.

Table 5.1. K-S test, MAE, and RMSE were applied to test fitting GEV, exponential Weibull, and beta distribution to 5, 6, 7, and 8 day running mean using the 1981-2000 period. The percentage of cell grids with $P_value > 0.01$ is used to determine the best fitting distribution. The standard deviation of the calculated MAE and RMSE is included.

<i>Data</i>	<i>Distribution fitting tests 1891-2000 period</i>	<i>Generalised extreme value</i>	<i>Exponentiated Weibull</i>	<i>Beta</i>
<i>5 days running mean</i>	P-value	78.4%	85%	99.9%
	MAE	0.006 ± 0.0009	0.006 ± 0.002	0.006 ± 0.0007
	RMSE	0.009 ± 0.001	0.009 ± 0.003	0.009 ± 0.0009
<i>6 days running mean</i>	P-value	72.3%	74.9%	99.9%
	MAE	0.007 ± 0.0009	0.007 ± 0.002	0.006 ± 0.0007
	RMSE	0.01 ± 0.001	0.01 ± 0.003	0.009 ± 0.0009
<i>7 days running mean</i>	P-value	70.5%	67.5%	99.5%
	MAE	0.007 ± 0.001	0.007 ± 0.002	0.007 ± 0.0008
	RMSE	0.01 ± 0.001	0.011 ± 0.002	0.01 ± 0.001
<i>8 days running mean</i>	P-value	68.1%	61.7%	96%
	MAE	0.008 ± 0.001	0.008 ± 0.002	0.007 ± 0.0008
	RMSE	0.01 ± 0.002	0.011 ± 0.003	0.011 ± 0.001

To demonstrate the method used to determine the return periods or recurrence intervals of LWE, we will use the five-day running mean as an example. Firstly, the running mean of daily wind speed data was calculated for five consecutive days across the spatial domain. The beta

distribution of the running mean was then used to calculate the return period for wind speed events that meet the cut-in threshold. This was accomplished through the following equation, which calculates the return period T for events with a magnitude equal to or less than x .

$$T = \frac{1}{F(x)} \quad (5.1)$$

T is the return period, $F(x)$ is the CDF of beta distribution.

The return period is defined as the chance of a threshold to occur in a given year. The high value of the return period indicates rare events. Some rare events can get up to “1 in 1000-year events”, which have a 0.1% chance of occurring in a given year. A 1 in a 1000-year event does not mean that an event will occur exactly every 1000 years, but it means that the event has a probability of occurring once every 1000 years. The return period calculation has been done on the historical and the two future periods. In Figure 5.8, a single-cell grid shows the return period curve for five days running mean. The black horizontal arrow shows the wind speed magnitude on the y-axis, and the corresponding vertical arrow indicates the return period on the x-axis.

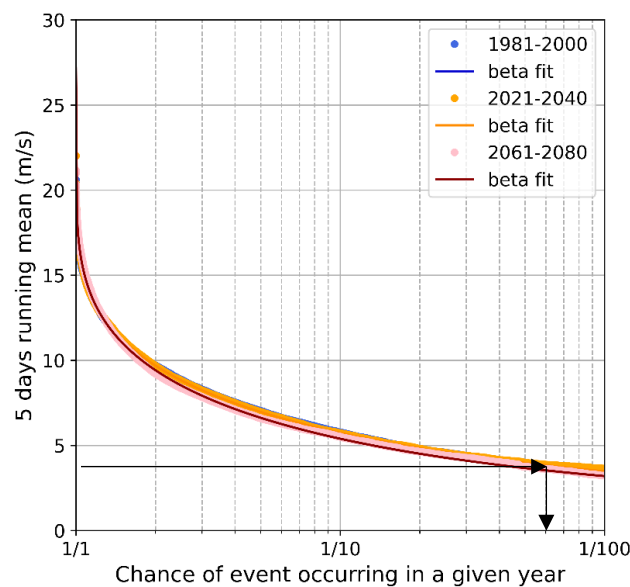


Figure 5.8. Return period calculation for 5 days running mean wind speed using beta distribution in a single cell grid for the 1981-2000 (blue), 2021-2040 (yellow), and 2061-2080 (red) periods. The bold black arrows refer to the 4m/s threshold (y-axis) and the corresponding return period (x-axis).

5.3.4.1 Return period for 4 m/s, 5 m/s, and 6 m/s using a five days running mean.

Using 5 days running mean wind speed as a representation of possible stress on the electricity grid from low wind generation, we have investigated in this section the probability of returning multiple cut-in wind speed thresholds in future periods. Consequently, we aim to understand the future risk for this event to reoccur and advise about future OWFs siting. Figure 5.9 shows the return periods of LWE with 5 day running mean wind speeds less than 4 m/s, 5 m/s, and 6 m/s. To understand the potential risk of more frequent return period, this study removes return period to greater than 50 years as it does not reflect a high risk. The return period of LWE is larger further from shore than in coastal regions, as more low wind speed datasets occur in the 20 years of data in locations near the coastline compared to open sea due to lower frictional drag across the open sea water's surface compared to near coastline surface. In the three periods shown in Figure 5.9 (a) 1981-2000, (b) 2021-2040, and (c) 2061-2080, the return period for 4 m/s less than 50 years has the smallest spatial coverage compared to the other two thresholds, as it is less likely to have 4 m/s in 5 days window compared to higher value wind speed thresholds. In the 2061-2080 period, the dispersion of return periods covers the majority of the east coast OWF locations between latitude 51°N to 57°N , while under higher thresholds such as 5 m/s and 6 m/s, there are even more locations with return periods ≤ 50 years. Figure 5.9 (g), (h), and (i) show the return period for 6 m/s extends over the entire EEZ, indicating a higher frequency of LWE events under 6 m/s compared to the other thresholds. The maximum return period values for 4 m/s and 5 m/s are 50 years, while for 6 m/s they are 38 years. To understand the change in the median for the spatial calculation of the return period shown in Figure 5.9, we compared the regional median for each of the four regions for the three climate periods in Figure 5.10. Figure 5.10 shows a trend of decreasing median return periods in the two future periods compared to the baseline period for 4 m/s, 5 m/s, and 6 m/s. This suggests a higher risk of more frequent LWE events in the future, except for a slight increase in the median in the

North region under 4 m/s and an increasing median in the West region under 5 m/s in the 2021-2040 period.

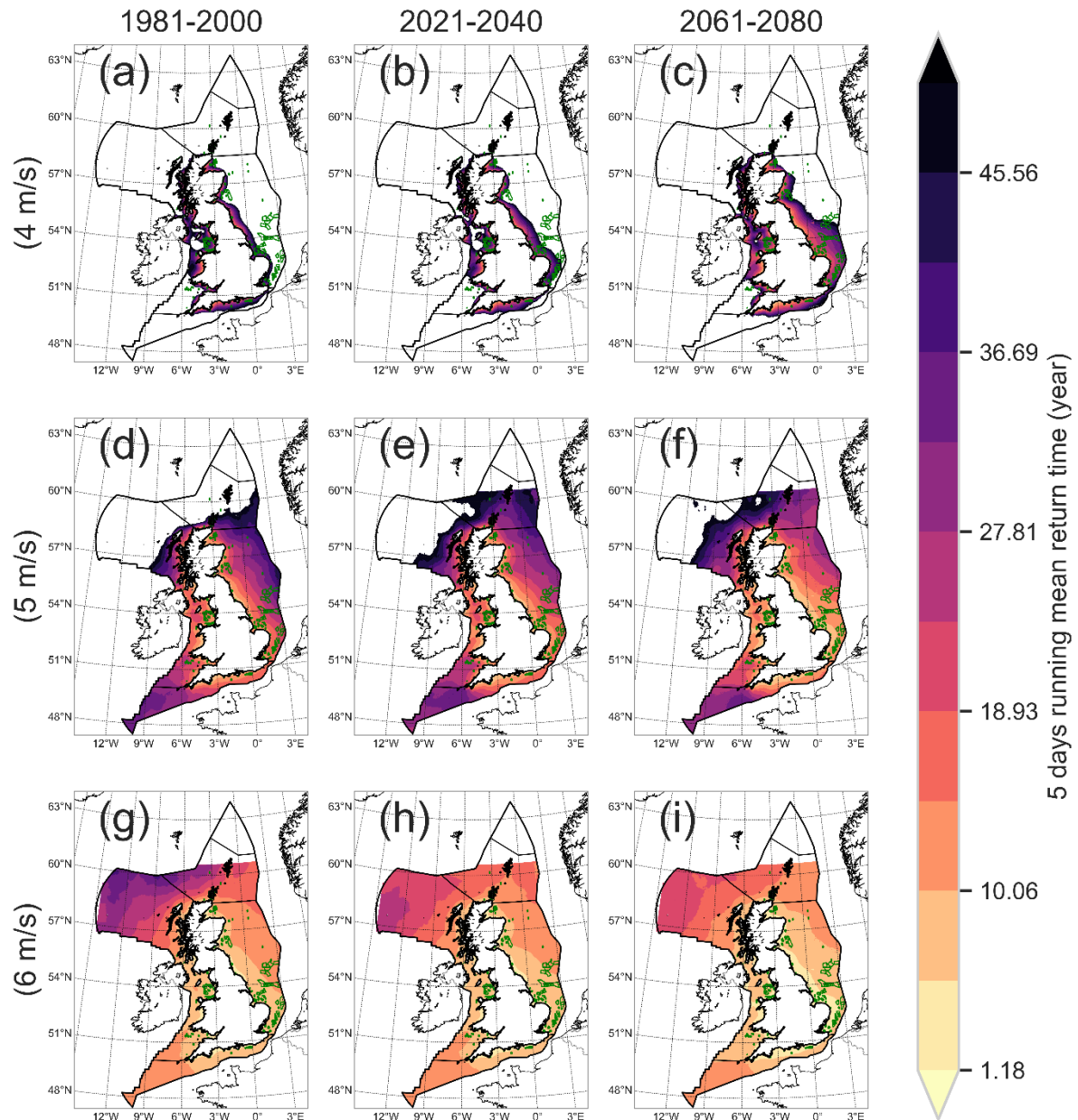


Figure 5.9. Return period for three different thresholds for five days running mean in years. Columns from left to right represent the 1981-2000, 2021-2040, and 2061-2080 periods. Rows from top to bottom represent 4m/s, 5m/s, and 6m/s. The green lines represent the fixed bottom wind farms and floating wind farms in UK offshore area. The data include all pre-planning, planning, construction, and operational phases.

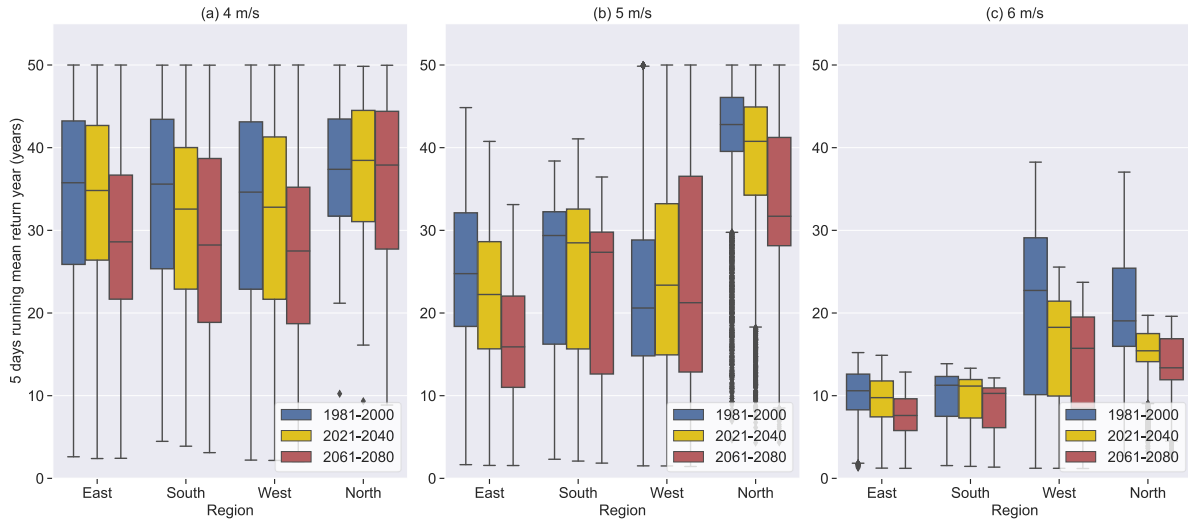


Figure 5.10. Box plot of return period of (a) 4m/s, (b) 5m/s, and (c) 6m/s using five days running mean for three periods (1981-2000 (blue), 2021-2040 (yellow), 2061-2080 (red)). Each plot's four comparison panels are the four regions, East, South, West, and North, respectively. The box holds the interquartile ranges (IQR), the midline represents the median. The thin vertical black line represents the rest of the distribution, except for points determined to be “outliers”. The whiskers show the maximum and minimum values. The points beyond the thin vertical lines are outliers.

In addition, the risk ratio (RR) is used to determine the ratio between the likelihood of the event occurring in 2021-2040 (RR1) and 2061-2080 (RR2) compared to the occurrence likelihood in the historical climate. The RR approach has been used to define extreme weather events and add confidence to the observed risk in a region [119], [120]. The RR is calculated as follows:

$$RR = \frac{(F / total_F)}{(H / total_H)} \quad (5.2)$$

Where RR is the risk ratio. H and F are the numbers of data less than the cut-in wind speed threshold in the historical and future periods, respectively. $total_H$ and $total_F$ are the total numbers of data available in the historical and future periods, respectively. $RR = 1$ means that the number of values less than a threshold does not affect the specific future period. $RR < 1$ means that the number of values less than a threshold has become less common in the future period. $RR > 1$ means that the number of values less than a threshold increases in the future. In

Figure 5.11, for the four regions, the RR values under 4 m/s, 5 m/s, and 6 m/s thresholds show a further increase in 2061-2080, similar to the increase from 2021-2040, indicating a monotonic of LWE risk with rising temperatures. In the West region, the median RR value for the 4 m/s threshold in the 2021-2040 period is 1. In the same period, the South region has a median RR value of 1 under 5 m/s and 6 m/s, indicating a lower risk of LWE events below the given thresholds in this climate period. On the other hand, there is a significant increase in risk in the East and North regions in the 2061-2080 period, with the RR of most cell grids above 1. The return period calculation is the likelihood of an event occurring in the distribution. On the other hand, the RR calculate the ratio between the number of data exceeding the threshold and the total number of data.

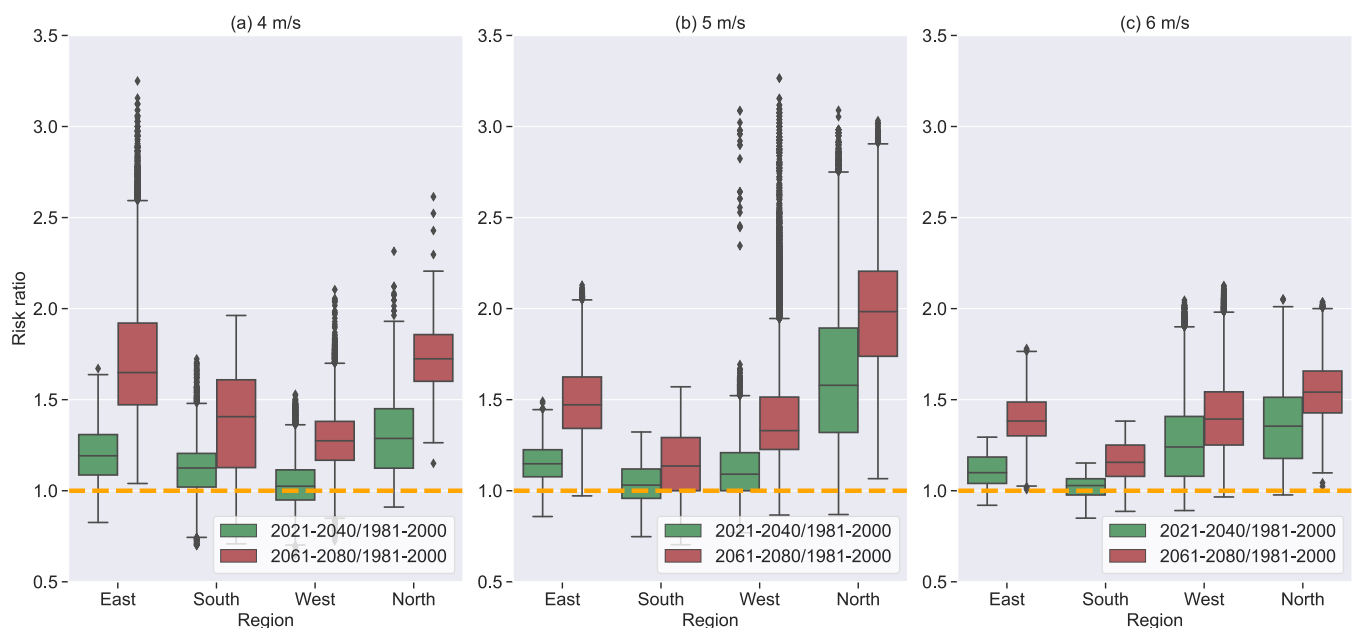


Figure 5.11. Box plot of RR for 2021-2040 relative to 1981-2000 (green) and 2061-2080 relative to 1981-2000 (red) calculated for (a) 4m/s, (b) 5m/s, and (c) 6m/s using five days running mean. Each plot's four comparison panels are the four regions, East, South, West, and North, respectively. The box holds the interquartile ranges (IQR), the midline represents the median. The thin vertical black line represents the rest of the distribution, except for points determined to be "outliers". The whiskers show the maximum and minimum values. The points beyond the thin vertical lines are outliers.

5.3.4.2 Return period for 4 m/s using 6, 7, and 8-day running mean.

Investigating the return period in a longer time window for the 4 m/s cut-in wind speed, considered the most common threshold in the literature [121], is crucial to estimating the future risk of LWE and understanding the likelihood of multiple LWE definitions to reoccur in the future. To this end, durations of 6, 7, and 8 consecutive days were defined as a set of time windows of interest. The running mean of the daily wind speed time series was calculated for each window, and the extreme value statistics were then applied to determine the return periods. Beta distributions were fitted for the four durations, as mentioned in Table 5.1. The return period for the 4 m/s threshold was calculated using the 6, 7, and 8-day running mean in Figure 5.12. As expected, it is less likely to cross the 4 m/s threshold for larger time windows and, additionally, in open sea areas. From Figure 5.9 (a), (b), and (c) and Figure 5.12, across all time windows for the 4 m/s threshold, the likelihood of LWE of this magnitude increases in open sea areas in the future. Figure 5.13 shows regional summaries of the spatial results of Figure 5.12 in a statistical format. In Figure 5.13 (a), for all regions, the six-day running mean shows that the 2061-2080 period has a notable decrease in median compared to the historical period, indicating an increased risk of more frequent low wind energy in all regions. The 2021-2040 period also shows a more marginal median change than the historical period. In Figure 5.13 (b) and (c) for 7 and 8 days, respectively, the 2021-2040 period shows a minor change in median compared to the historical period, except for the North region using the eight-day running mean, which indicates an increasing LWE risk in the two future periods compared to the historical period. The 2061-2080 period shows a decrease in median in the South and North regions for the seven-day running mean and, in the South, West, and North regions for the eight-day running mean.

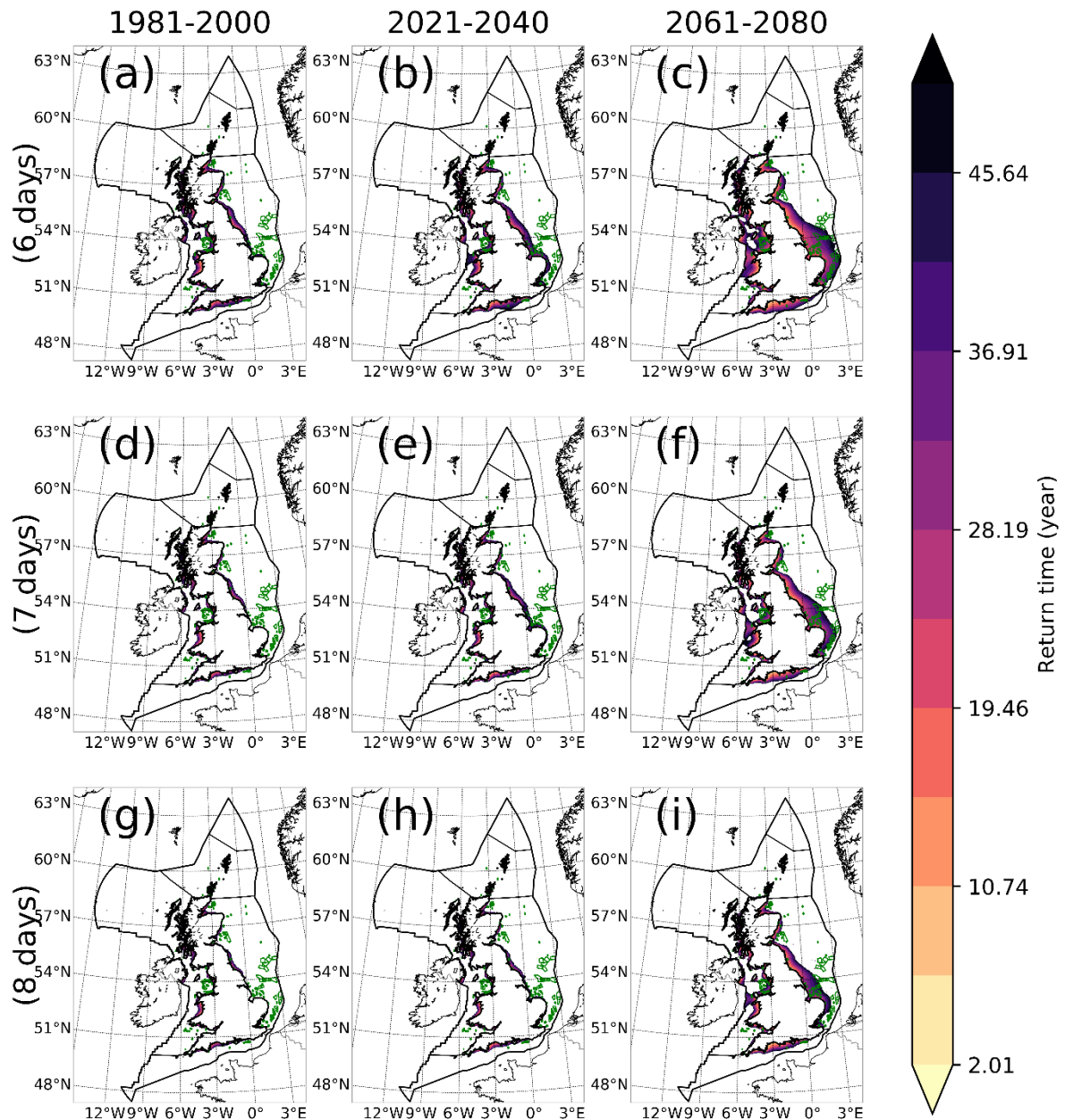


Figure 5.12. Return period for 4m/s in years using 6, 7, and 8 days running mean. Columns from left to right represent the 1981-2000, 2021-2040, and 2061-2080 periods. Rows from top to bottom represent a running mean of 6, 7, and 8 days. The green lines represent the fixed bottom wind farms and floating wind farms in UK offshore area. The data include all pre-planning, planning, construction, and operational phases.

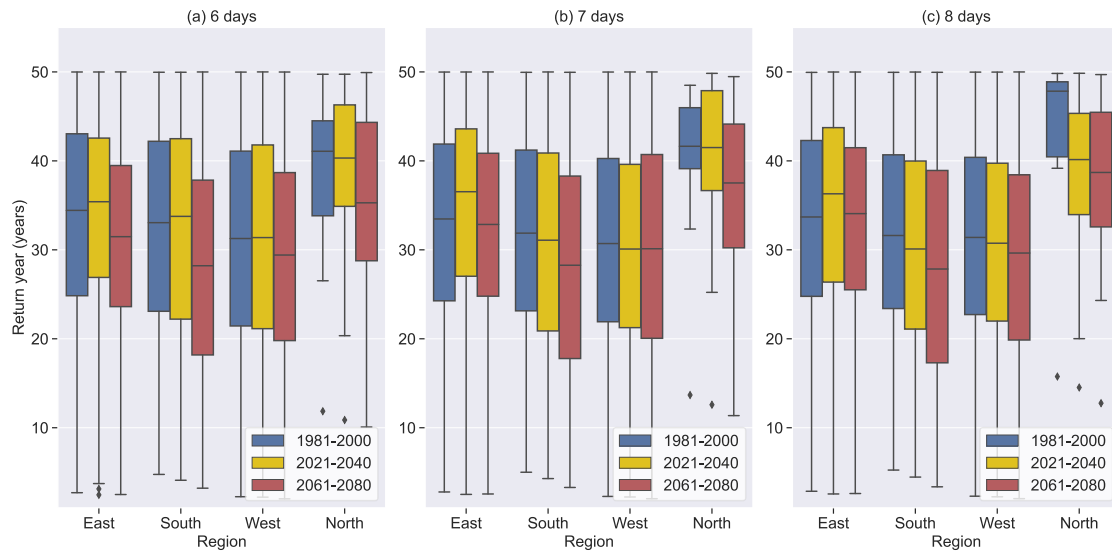


Figure 5.13. Box plot of return period of 4m/s using (a) 6 days, (b) 7 days, and (c) 8 days (running mean) using three periods (1981-2000 (blue), 2021-2040 (yellow), 2061-2080 (red)). Each plot's four comparison panels are the four regions, East, South, West, and North, respectively. The box holds the interquartile ranges (IQR), the midline represents the median. The thin vertical black line represents the rest of the distribution, except for points determined to be “outliers”. The whiskers show the maximum and minimum values. The points beyond the thin vertical lines are outliers.

In Figure 5.14, the RR of falling below the 4 m/s wind speed threshold is calculated for three running mean time windows: 6, 7, and 8 days. As seen in Figure 5.14 (a), (b), and (c), the 2061-2080 period exhibits higher median RR compared to the 2021-2040 period, signalling an increased risk of reaching the 4 m/s threshold in the latter period. The West region in Figure 5.14 (a), (b), and (c) consistently has the lowest risk for both the 2021-2040 and 2061-2080 period. In the 2021-2040 period, the West region's median RR remains at one across all time windows, showing no change in risk compared to the historical period, and in 2061-2080 has a median RR of approximately 1.3.

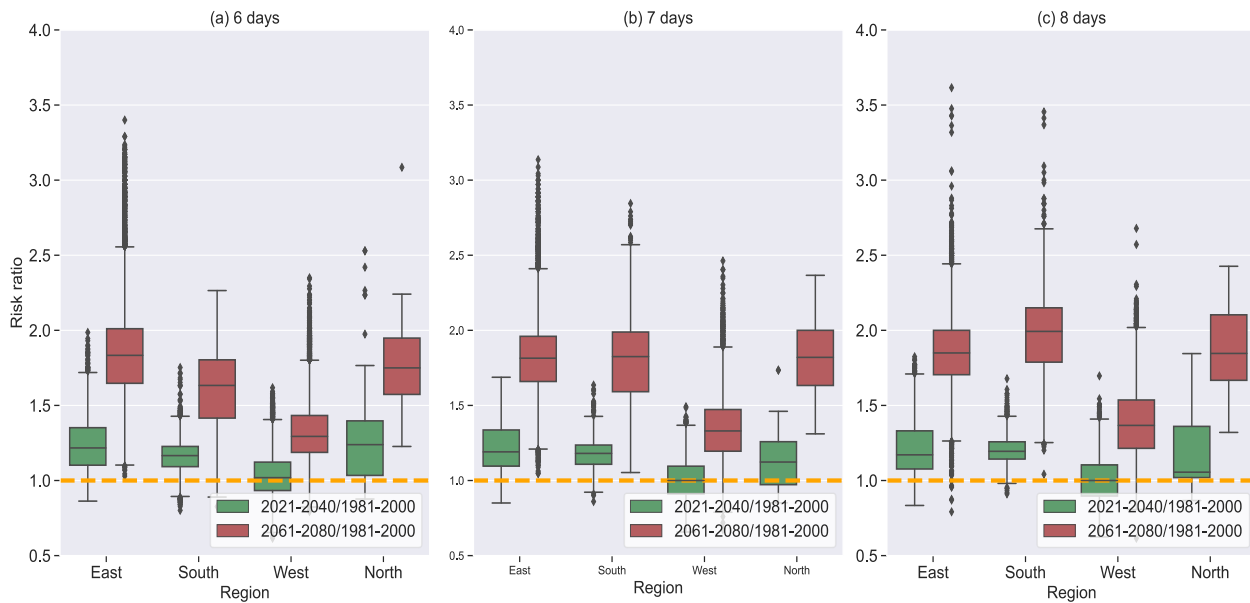


Figure 5.14. Box plot of RR falling below 4m/s for 2021-2040 relative to 1981-2000 (green) and 2061-2080 relative to 1981-2000 (red) calculated for (a) 6 days, (b) 7 days, and (c) 8 days (running mean). Each plot's four comparison panels are the four regions, East, South, West, and North, respectively. The horizontal orange line point toward value =1, representing no change threshold. The box holds the interquartile ranges (IQR), the midline represents the median. The thin vertical black line represents the rest of the distribution, except for points determined to be “outliers”. The whiskers show the maximum and minimum values. The points beyond the thin vertical lines are outliers.

5.4 Discussion

We aimed to understand the future change in low wind speed using four different analyses: collectively, aiming to investigate the future change in low wind speed. Examining the 5th, 6th, 7th, 8th, and 10th percentiles of daily mean wind speed aims to ascertain that the 8th percentile encompasses a range of wind speeds throughout all seasons, including the most prevalent cut-in wind speed values (< 6 m/s). The findings show that the summer season has the lowest wind speeds, as evidenced by the CDF and 8th percentile, reaching between 5% and 25% in all regions except the South region. Additionally, the summer season has the longest durations of low wind speed (< 4 m/s). Moreover, it is noted that the two future periods in the autumn season also drop in the majority of the low wind speed durations compared to the historical period, potentially representing an extension of the summer season LWE in the future, except for 2061-

2080 period the durations show a decrease compared to the historical period in the South region. These findings emphasise the importance of combining wind with other renewable energy sources, such as solar and hydropower and having the ability to manage electricity demand effectively during times when wind speeds are low, particularly during the summer season.

Using five-day running mean data in return period analysis showed that the likelihood of experiencing LWE for wind speeds of 4 m/s, 5 m/s, and 6 m/s is higher near the shore in OWF locations than in open sea locations. In the three climate periods, most locations in the EEZ that utilise OWT with a cut-in wind speed of 6 m/s are at risk of frequent LWE with a return period of up to 20 years. Moreover, using a five-day running mean data, the North and West regions are the only regions with a negligible change in the return period regional median in two future periods compared to the baseline period for the 4 m/s and 5 m/s thresholds, respectively. In an attempt to assess more extreme conditions for LWE, the North region remains recommended 4 m/s in 6 and 7 days running mean in the 2021-2040 period compared to the historical period, and the West region has the lowest risk for more frequent 4 m/s in 6, 7, and 8 days for the 2021-2040 period compared to the historical period.

5.5 Extreme low wind speed conclusion remarks

Motivated by the UK government's efforts for a more sustainable energy model to meet its net-zero target, this chapter delves into the topic of LWE and its impact on wind turbine energy production. We aim to provide a comprehensive understanding of the characteristics and risks of LWE in the future through four analysis that covers various risks of low wind speed, such as change in the mean of the distribution, future change in the left tail of the distribution under specific low wind speed percentile, the LWE persistence occurring, and the future change in return period occurrence of LWEs. To recommend locations resilient to future LWE, the

research compares four regions (East, South, West, and North); collectively, the regions cover the UK EEZ.

The main findings of this study can be summarised as follows:

- A seasonal investigation for the percentile corresponding to the most common range of low wind speed found that the 8th percentile was the best to cover the most common range of cut-in wind speed (3 m/s to 6 m/s) across seasons, as a result for the future change calculation for the 8th percentile of wind speed, the future planning for future OWF installation must consider alternative energy production source in summer season to meet the demand in East, West, and North EEZ regions.
- The duration of low wind speed was investigated in a seasonal period, confirming the risk of persistent low wind speed in summer and autumn seasons, where 2061-2080 period show an increase occurring compared to the historical period in most duration across all regions.
- The return period calculations for the 4 m/s threshold for the historical and two future periods using the Beta distribution, which was found to fit best the 5, 6, 7, and 8 days running mean dataset, resulted in emphasising the importance of considering future planning of wind turbines with cut-in wind speed < 4 m/s in locations near to the coastline. Moreover, the research finding found a similarity between the future change in the statistic region median for the calculated return period and the corresponding RR calculations, leading to recommend the South as a region with a lower risk of the more frequent occurrence of cut-in wind speed threshold in the 2021-2040 period compared to historical period using 5 m/s and 6 m/s cut-in wind speed thresholds and recommend the West region for 4 m/s investigation in 6, 7, and 8 days in the same future time period.

Certain regions within the UK EEZ are susceptible to an increased risk of more severe extreme LWE, while other regions may experience reduced risks. Consequently, when

installing future OWTs, a careful assessment and evaluation of suitable locations are imperative. Factors such as the anticipated intensity of LWE events should be carefully considered to ensure the optimal siting of these turbines.

Chapter 6 Cut-out wind gust and extreme wind gust investigation

6.1 Overview

This chapter uses the 2.2 km UKCP18 hourly maximum wind gust datasets. The statistical characterisation of extreme wind gusts is assessed using multiple distributions, and a Beta distribution is found to predict the hourly wind gust data adequately. Risk ratio (RR) and relative change (RC) have been used to investigate changes in extreme wind loading on wind turbine structures (50-year return period, hereafter U_{50}) and the no-operational wind gusts that can decrease the wind turbine operational performance at 35 m/s. The work described within this chapter was published in IEEE GREEN TECH 2023 conference and IEEE PES GM 2023 conference (**Abdelaziz et al. 2023c** and **Abdelaziz et al. 2023d** from Related Publication section).

6.2 Introduction

Exposing wind turbines to extreme high wind speed can lead to failure in the wind turbine structure [122] and acceleration in the wear of wind turbine components which can also increase the fatigue load on the wind turbine structure [26]. Therefore, future offshore wind farms (OWF) locations must be resilient to changes in future weather, given current wind turbine design specifications. This chapter investigates high wind gust in the wind energy field, which is represented into two thresholds: 1- cut-out wind gust threshold (defined by exceeding the 35 m/s wind gust). Beyond 35 m/s cut-out wind gust turbines stop generating power to avoid damage and enter a self-protective state, such as feathering blades or braking to reduce

mechanical stress. Understanding how often these speeds are exceeded helps design these protective measures more effectively. Using an exceedance value of 35 m/s as a threshold is primarily related to assessing wind turbines' operational limits and protective measures rather than indicating a direct structural risk. Manufacturer may choose to specify different values for this threshold and 35 m/s is employed as indicative for the 17 MW turbine considered. On the other hand, we use extreme wind gust threshold (defined by a 50-year return period and representing the wind turbine structure loading risk) [123]. Both no operational risk and structure loading risk are important to locate the best locations to site OWF and will be used in the siting model in Chapter 7.

By investigating the thresholds in future wind data, it is possible to quantify the effect that likely future extremes high wind could have on wind turbine operation in a specific location, thereby informing the optimal siting of future OWF in the UK. According to the International Electrotechnical Commission (IEC) 61400-1 standard, U_{50} is a crucial determinant of wind turbine structural loading due to extreme high wind speed. It is used to inform wind turbine design in a specific area [123]. In an area prone to extreme wind speed, U_{50} is set high, which will increase the capital cost value. More accurate siting of wind turbine leads to installation in locations less at risk from EWE and limits over-engineering of wind turbine for a given deployment location, thereby potentially reducing financing costs for a specific project capital cost. A wide range of location diversity exists in investigating extreme high wind speeds using historical models or observational data. For example, on the east coast of New Jersey, Debnath et al. [124] used the available observation data from floating lidars to assess extreme events, finding for 100 m height wind speed that almost 100 events occur throughout the year. In Bangladesh [125], simulations of tropical cyclones produce exceedance probability estimates for extreme wind (gust). It has been found that Khulna, Barisal, and Chittagong provinces will experience maximum wind speed over cyclonic storm conditions > 25 m/s, and areas within 30

km of the coastline are predicted to experience gust speeds > 33 m/s. Laurila et al. [126] studied extreme wind speed using the fifth-generation ECMWF atmospheric reanalysis wind dataset in North Atlantic and Europe from 1979 to 2018. The 98th percentile was used to define the extreme wind. The same research found a seasonal variation with the strongest winds over the ocean and during winter. In addition, climate change models have been used in some regions such as North America [127] and Europe [128], [129] to investigate extreme wind speed events. On the other hand, climate change impacting cut-out wind speed threshold (high wind speed no-operation threshold) is analysed in terms of changing magnitude in future climate scenarios [130]. From the literature, we found a need for spatial analysis for future changes in cut-out wind gusts and U_{50} in the UK EEZ. We focus on climate change impacting future OWF siting in four main regions covering the UK exclusive economic zone (EEZ) as defined in chapter 3, section 3.4. The contributions of this chapter are summarised as follows:

- Investigating the likelihood of a 35 m/s wind gust event to occur in the future and calculate the future change of 35 m/s return period in two future time windows compared to the historical period. Moreover, Investigating the future changes in U_{50} in two future time windows compared to the historical period (relative change calculations (RC)).
- Investigating the exceeding risk for the 35 m/s threshold and for the wind gust corresponding to U_{50} (risk ratio (RR)) helps to inform the spatial locations most prone to wind energy reduction in the UK EEZ.

The rest of the chapter is organised as follows: Section 6.3 includes the method to calculate the 35 m/s return period, U_{50} , and assess the future change (RC) and the exceeding change (RR). Section 6.4 presents the results of the RC and the RR. Section 6.5 concludes the results.

6.3 Methods

This section tests the best-fitting distribution to wind gust data using nonparametric tests. The most common wind turbine no-operation threshold (cut-out wind gust 35 m/s) is used [131]. The U_{50} and the return period corresponding to a 35 m/s wind gust is introduced, and the RC and RR methods to investigate future changes are included.

6.3.1 Hourly wind gust best fit.

This chapter uses the surface maximum wind gust data scaled to wind turbine hub height, see equation (3.2), which is the maximum 10-minute wind gust, indicating that it is a sustained gust rather than a short, sharp burst of wind. There are a series of 10-minute periods in every 1-hour lapse. Each period of 10-minutes has its wind speeds, and the fastest of those within that 1-hour lapse becomes the 1 hour gust speed. The ERA5 wind gust is defined as the maximum 3-second wind speed at a height of 10 meters, as specified by the WMO. This 3-second gust is computed at each time step, with the maximum value retained through post-processing. In this research, we used mean wind speed datasets described in Chapter 3 (Data Preparation) to validate the wind speeds within the UK's Exclusive Economic Zone (EEZ), we compared them against ERA5, ultimately selecting the 01 ensemble for further analysis. Since the mean wind speed and maximum wind gust are extracted from the same climate model, we will use ensemble 01 for maximum wind gust in this chapter and to be able to combine all results from both chapters in one model that predicts future siting. Estimating the frequency and magnitude of EWE is an essential part of energy development as it increases the stockholder's confidence in financial and risk analysis.

The UKCP18 CPM for wind gusts has been used in multiple studies in the UK and Europe [132], [133], [134]. It shows a good representation of wind gusts by comparing them to the ERA-Interim dataset. The main findings from [133] and [134] are 1- The ERA-Interim dataset tends to underestimate the frequency and intensity of wind speeds above 35 m/s. This

underestimation occurs because ERA-Interim's coarser resolution does not capture the small-scale atmospheric processes that generate very high wind speeds. 2- In contrast, the UKCP18 CPM provides a more accurate simulation of wind speeds exceeding 35 m/s due to its finer resolution (2.2 km). This higher resolution allows the model to capture critical mesoscale phenomena, like sting jets, which are often associated with extreme wind speeds. These phenomena are poorly resolved in ERA-Interim due to its coarser grid spacing. 3- The finer resolution of the CPM allows for a better representation of local features, such as topography and mesoscale storm structures, which can significantly influence wind speeds. As a result, the CPM can simulate higher wind speeds and more accurately predict windstorms with gusts above 35 m/s, especially in regions where these events are driven by sting jets or intense cyclonic systems.

Due to topographical and geographical differences, wind resources can vary from one location to another. Therefore, spatial assessment of extreme high wind speed is necessary to site OWF [135]. Using the baseline period, we use multiple probability density functions to assess wind gust variability and uncertainty; the main goal is to determine the best fit for the wind gust distribution. Four distributions have been used to spatially predict hourly maximum wind gust statistics at a hub height of 151 m, Gamma [136], Generalised extreme value (GEV) [137], Exponential Weibull [116], and Beta [117]. The Kolmogorov-Smirnov (K-S) test and Cramér-von Mises [118] have been used to test the goodness of fit for all data. Both tests use the P-value to indicate that the wind gust data conforms with the given distribution. If the P-value is lower than a threshold of 0.01 (99% confidence interval), we reject the null hypothesis and conclude the data are not distributed according to the tested distribution. In Table 6.1, P-values are shown for baseline periods. The wide variety of shapes in beta distribution added flexibility to the distributions. The analysis reveals that the Beta distribution produces the

highest P-value > 0.01 compared to the other three distributions, equal to 0.28 in the K-S test and 0.19 in the Cramér-von Mises test.

Table 6.1. Cramer-Von Mises and K-S tests were applied to distributions using the 1891-2000 period.

Tests	Gamma	GEV	Exponentiated Weibull	Beta
Cramér-von Mises test	1.43*10 ⁻⁹	6.02*10 ⁻⁹	3.49*10 ⁻⁷	0.19
K-S test	4.07*10 ⁻⁶³	7.62*10 ⁻⁷⁴	0	0.28

6.3.2 Climate change calculations for 50-year return period and 35 m/s cut-out wind gust.

Firstly, the hub height hourly maximum wind gust data are used across the spatial domain. The beta distribution of the maximum wind gust data was then used to calculate the return period for wind gusts that meet the threshold. This was accomplished through the following equation, which calculates the return period T for events with a magnitude equal to or greater than x .

$$\text{Return time } (T) = \frac{1}{1 - F(x)} \quad (6.1)$$

$F(x)$ is the CDF of beta distribution.

The return period calculation has been done on the historical and the two future periods. In Figure 6.1, a single-cell grid shows the return period curve for the hourly maximum wind gusts dataset. The black arrow pointing upward refers to the wind gust threshold (m/s) corresponding to the U_{50} and the purple arrow pointing toward the south refers to the return period corresponding to the 35 m/s wind gust threshold. The U_{50} and the return period corresponding to 35 m/s has been calculated spatially using Beta distribution for the 1981-2000 period in Figure 6.2 (a) and (b), respectively. In Figure 6.2 (a), the wind gust corresponding to U_{50} has and increasing value in open-sea areas than near coast areas, the contradict is in Figure 6.2 (b), where the return period corresponding to 35 m/s has decreased return period in open-

sea areas. Both results show an increased risk for more intense and frequent wind gusts in open-sea areas, located above latitude 57° N.

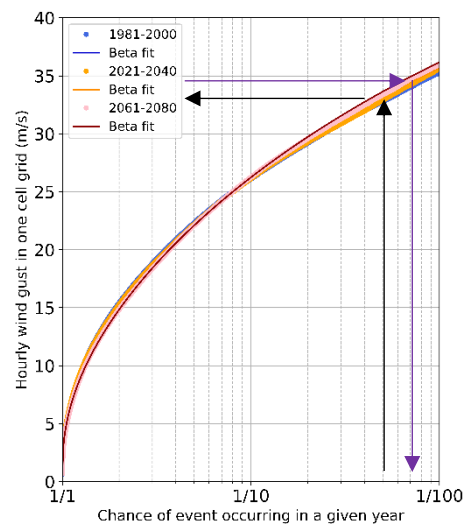


Figure 6.1. Return period for wind gusts using beta distribution in a single cell grid for the 1981-2000, 2021-2040, and 2061-2080 periods. The bold black lines refer to the 50 year return period (U_{50}) (x-axis) and the corresponding wind gust (y-axis), and the bold purple line refers to the return period corresponding to 35m/s wind gust (y-axis) and the corresponding return period (x-axis).

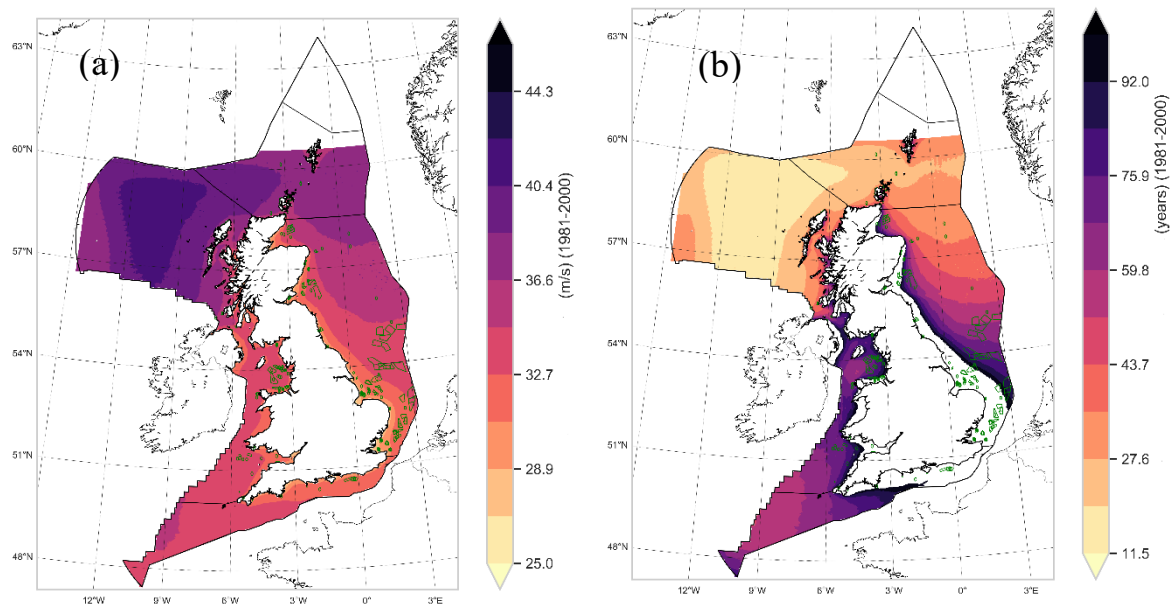


Figure 6.2. (a) The wind gust (m/s) corresponding to 50 year return period. (b) The return period corresponding to 35m/s in (years) using the 1981-2000 period; results from greater than 100 return periods have been masked. Black outer boundaries represent the EEZ, and black internal boundaries are the four regions. The green lines represent the fixed bottom wind farms and floating wind farms in UK offshore area. The data include all pre-planning, planning, construction, and operational phases.

In this chapter, we consider the changing magnitude of the U_{50} wind gusts and 35 m/s return period in the future, the RC of climate change signals is calculated as in equation (4.2). In addition, we are looking at the future changes in the probability of exceeding 35 m/s and U_{50} . The RR has been calculated as follows:

$$RR = \frac{(F/total_F)}{(H/total_H)} \quad (6.2)$$

Where RR is the risk ratio. F and H are the numbers of wind gust data exceedance the U_{50} and 35 m/s thresholds in the future and historical periods, respectively. $total_F$ and $total_H$ are the total numbers of data available in the future and historical periods, respectively. RR1: Is the risk ratio of 2021-2040 / 1981-2000, and RR2: Is the risk ratio of 2061-2080 / 1981-2000.

6.3.3 Extreme wind speed manufacturer standard threshold

Additional costs can arise from higher capital expenditure (CapEx) of wind turbine. The purchase of wind turbine, grid connections, and installation of foundations calculates CapEx. It is scaled with reference wind speed (U_{ref}) [13]. According to the International Electrotechnical Commission (IEC 61400-1) standard of a wind turbine, U_{ref} is set as a key determinant of wind turbine structural loading due to extreme wind speed and hence its used to deploy wind turbine design in specific area [123], so in a prone area to extreme wind speed the U_{ref} is set high and that will lead to increase the CapEx value.

Extreme wind speed events have been related to wind turbine manufacturer standard thresholds [123]. According to the IEC 61400-1, extreme wind conditions are accounted for in the design for all three wind turbine classes, I, II, and III, by defining hub-height reference wind speed (U_{ref}) [123]. The U_{ref} represent the engineering threshold for wind turbine to withstand extreme wind conditions, and its equal to 50, 42.5, and 37.5 (m/s) for classes I, II, and III,

respectively. It is calculated as a five time's annual mean wind speed in the specified location. U_{ref} is set to be $\geq$ 50-year return period (U_{50}) wind speed. Pryor and Barthelmie [13] investigated how the manufacture estimation for the extreme wind load can affect wind turbine cost globally. The study compares the U_{ref} calculated using five times mean wind speed (as specified in IEC wind turbine design standards) with U_{50} calculated from forty years of hourly 100 m wind speed data from the ERA5 reanalysis. As a result, for more than half of all grid cells, U_{ref} exceeds any of the U_{50} estimates by >10.6 m/s. The study concludes that using the five times the mean wind speed measurement to estimate the U_{ref} is a conservative in engineering aspect and can lead to an overestimation of the required capital expenditures for wind turbine. The study only considers current climate conditions and did not account for future climate change.

In this chapter, the hourly mean wind speed at 151 m hub height is used to calculate the U_{ref} . We identified the difference between U_{ref} , defined by five times the annual mean and the U_{50} to determine the accuracy of identifying the extreme loading risk on the OWF in the three periods. In Figure 6.3, the difference between U_{ref} and U_{50} is calculated for (a) 1981-2000, (b) 2021-2040, and 2061-2080 periods in the UK EEZ. It is found that 98% of locations in the baseline and the 2021-2040 periods have over 11 m/s of U_{ref} exceeding U_{50} . In the 2061-2080 period, there is a decrease in the percentage of locations $\sim 97\%$ that have 11 m/s of U_{ref} exceeding U_{50} . The smallest wind speed differences lie near coastlines and gradually increase toward the open sea. Our results confirm Pryor and Barthelmie [13] results, as all locations exhibited an increase for U_{ref} than U_{50} . In the present and future periods, considering the U_{50} rather than U_{ref} in defining the wind turbine extreme loading is more accurate in identifying current and future risks on OWF structure in the UK EEZ.

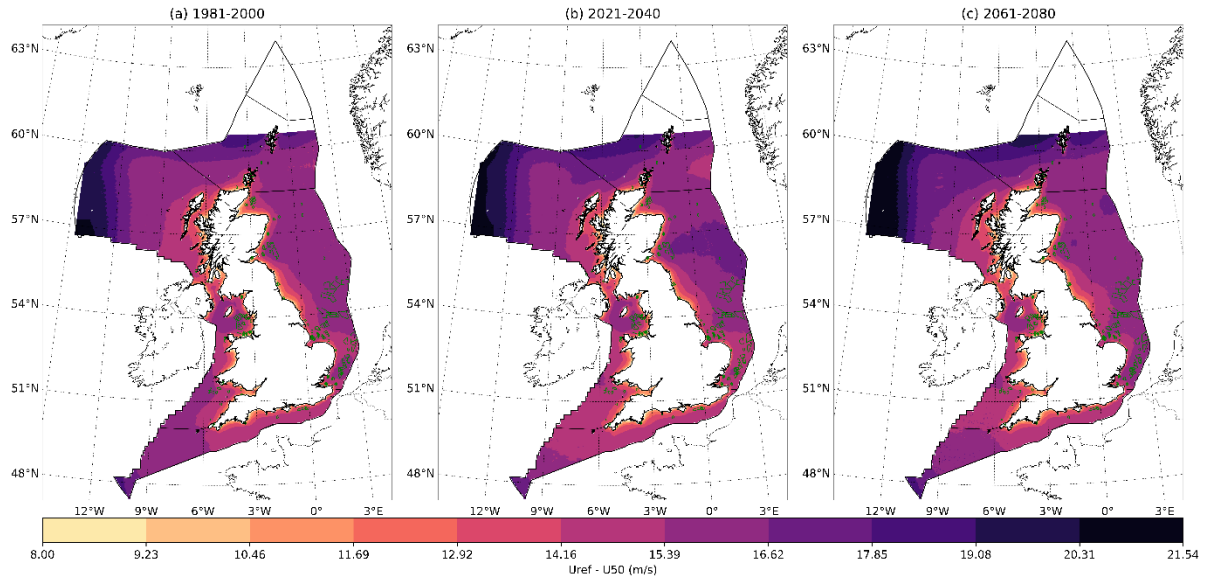


Figure 6.3. The difference between reference wind speed (U_{ref}) and 50-year return period wind speed (U_{50}) using Beta distribution.

6.4 Results

This section summarises the results for both U_{50} and 35 m/s using RC and RR calculations.

6.4.1 50-year return period

(a) The U_{50} RC: We investigated the extreme gust loading on wind turbine structures in two future periods by calculating the wind gust corresponding to U_{50} in the three climate periods. The RC calculation gave a good indication for increasing/ decreasing changes in two future periods. The wind gusts RC to U_{50} are shown in Figure 6.4 (a) 2021-2040 relative to 1981-2000, (b) 2061-2080 relative to 1981-2000, and (c) 2061-2080 relative to 2021-2040. In Figure 6.4, a positive relative difference (red shades) indicates that the wind gust threshold corresponds to U_{50} has an increased risk in the future period compared to the baseline period (fewer advantageous sites). At the same time, negative values show that the wind gust thresholds in future periods are smaller than the baseline period, which indicates decreasing risk (more advantageous sites). Most locations in Figure 6.4 show marginal positive changes between periods. In 2021-2040 relative to 1981-2000, Figure 6.4 (a) shows a desirable area for siting OWF in the East region above latitude 54° N and the north of the UK. Figure 6.4 (b) and

Figure 6.4 (c) show more locations in the East region experiencing positive RC $\sim 2\%$. Most negative RC locations in 2061-2080 relative to 1981-2000 lay above latitude 57° N, indicating a consistent trend to lower U_{50} values up to 5% decrease.

In Table 6.2, we show the percentage of locations with increased risk for larger return wind gusts regardless of the value, which is less than 10% in Figure 6.4 for U_{50} and less than 50% in Figure 6.8 for 35 m/s return period. The U_{50} in (row 1), and a more frequent return period for 35 m/s in (row 2) is calculated separately for the four regions (the number of cell grids is calculated according to the cell grid that shows positive or negative signs without considering the value of the change). For U_{50} and 35 m/s, the increased risk is presented in RC positive change (+) and negative change (-), respectively. Table 6.2 (row1: U_{50}) summarise the spatial RC calculations shown in Figure 6.4 by counting the number of cell grids with positive and negative change and normalising the results for each of the four regions separately. We can conclude that the risk for a return period of 35m/s is higher than U_{50} . Generally, the table shows regions with increased risk (whether it is a small risk of 10% in U_{50} or a large risk as in the 35m/s return period). The main aim of the table is to detect the spatial extent of the increase or decrease signal of change in the future for current OWFs and understand which region has the larger number of locations with increased change compared to what they already experienced in the past.

In U_{50} , using 2021-2040 relative to 1981-2000, the East region is the most favourable, and the South region is at increased risk, with 14.3% and 99.7% of the cell grid having an increased risk for higher wind gusts in the future. In 2061-2080 relative to 1981-2000, the North and South regions have the lowest (0.2%) and the highest (49.3%) risk, respectively. In 2061-2080 relative to 2021-2040, the South region has the least risk, and the East region has the highest risk for more locations with increased wind gusts in the future.

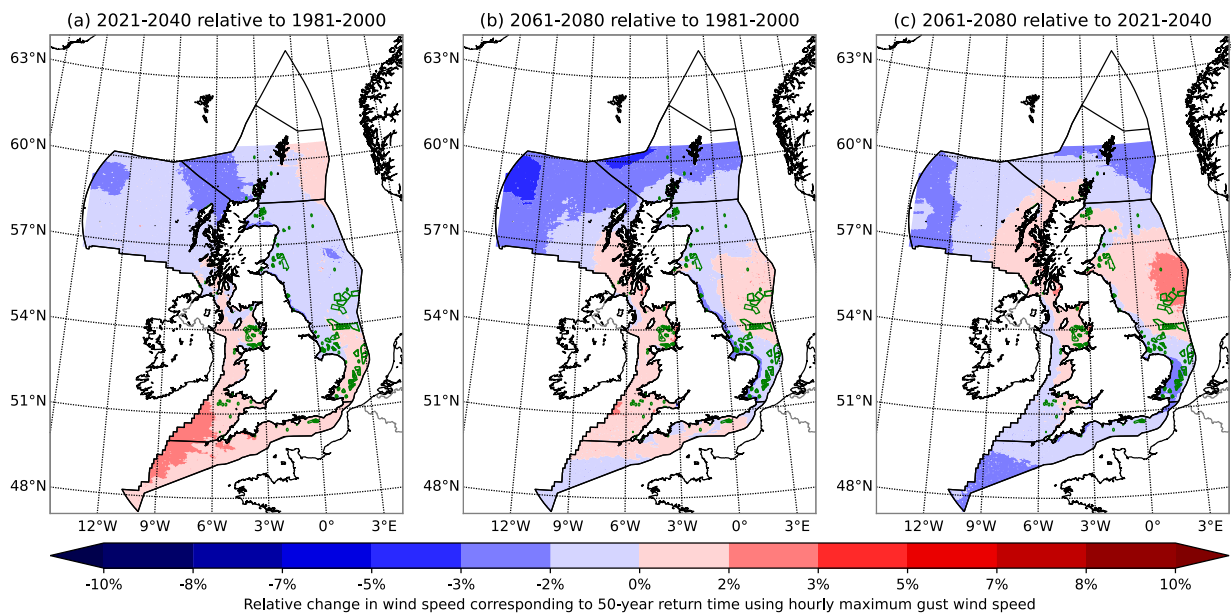


Figure 6.4. RC in wind gusts corresponds to 50 year return period (U_{50}). (a) 2021-2040 relative to 1981-2000, (b) 2061-2080 relative to 1981-2000, and (c) 2061-2080 relative to 2021-2040. Black outer boundaries represent the EEZ and black internal boundaries are the four regions. The green lines represent the fixed bottom wind farms and floating wind farms in UK offshore area. The data include all pre-planning, planning, construction, and operational phases.

Table 6.2. Percentage of locations with increased risk. (+) indicates that the percentage of cell grids that hold a positive RC is considered an increased risk in 50 year return period (U_{50}). (-) indicates that the percentage of cell grids that hold a negative RC is considered an increased risk at 35m/s. The calculations are done separately for the four regions (E: East, S: South, W: West, N: North).

RC percentage of increased risk locations (%)												
	2021-2040 relative to 1981-2000				2061-2080 relative to 1981-2000				2061-2080 relative to 2021-2040			
	E	S	W	N	E	S	W	N	E	S	W	N
U ₅₀ (+)	14.3	99.7	23.6	25.9	35.7	49.3	32	0.2	65	0.3	30.6	10.8
35m/s (-)	20.9	99.7	24.6	10.4	42.6	72.3	28.9	0.1	68.6	0.5	26.4	6

Figure 6.5 shows a statistical comparison between the East, South, West, and North regions. The highest median and most extensive range of wind gusts correspond to U_{50} occurs in the West region for the three climate periods. Also, the North region has the second median for the three periods. At the same time, the West and North regions have a consistent decrease in region median in the two future periods. On the other hand. The lowest median region values for all three periods were observed in the East and South regions. In the East region, the 2021-

2040 period exhibited a decrease in median values compared to the baseline period, while the South region experienced an increase. On the other hand, the 2061-2080 period showed an increase in median values for the East region and a decrease for the South region compared to the baseline period. Although both the West and North regions show the U_{50} wind gust threshold will decrease in two future climate periods; they remain the highest wind gust value compared to other regions.

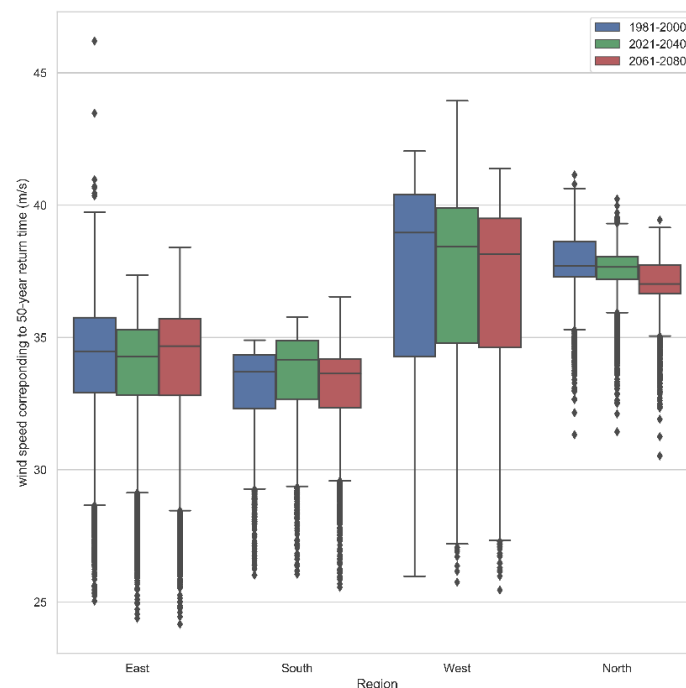


Figure 6.5. Box plot for wind gusts corresponding to 50 year return period (U_{50}), the results are in (m/s). The four panels are regions East, South, West, and North. (1981-2000 (blue), 2021-2040 (green), 2061-2080 (red)). The box holds the interquartile ranges (IQR), the midline represents the median. The thin vertical black line represents the rest of the distribution, except for points determined to be “outliers”. The whiskers show the maximum and minimum values. The points beyond the thin vertical lines are outliers.

(b) The U_{50} RR: We are taking the U_{50} threshold from the baseline period and working out the probability of meeting or exceeding that threshold in future periods. $RR = 1$ means that exceeding a certain threshold does not affect the specific period. $RR < 1$ means that the risk of exceedance of a certain threshold is decreased in the future. $RR > 1$ means exceeding a certain threshold has become more common in the future. In Figure 6.6, the spatial calculations for (a)

RR1 and (b) RR2 are shown and reflected in the statistical median in Figure 6.7. Figure 6.7 shows the RR1 and RR2, representing the ratio between historical period thresholds and 2021-2040 (blue) and 2061-2080 (green), respectively. There is a pronounced increase in RR1 and RR2 region median in the South region compared to the other three regions. In addition, the North region has the most significant decrease in the RR region median. The result confirms the increased U_{50} risk detected in RC calculation.

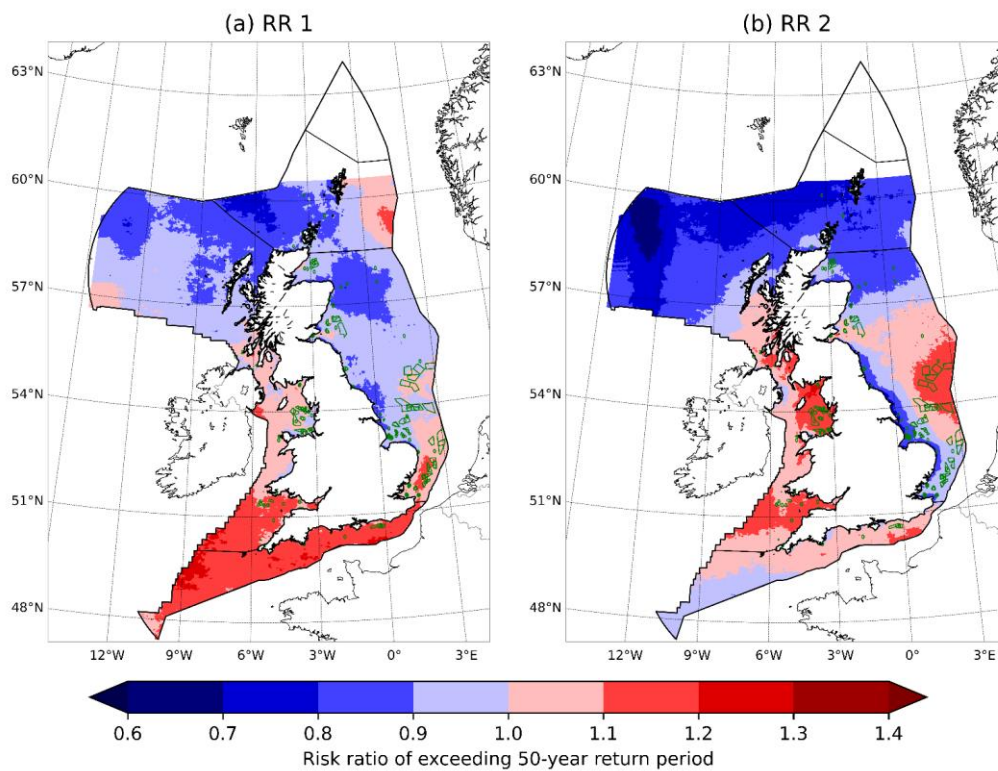


Figure 6.6. RR of wind gust corresponding to 50 year return period (U_{50}). (a) RR for 2021-2040 against 1981-2000, (b) RR for 2061-2080 against 1981-2000. The red shades represent the increased risk in RR, and the blue shades represent the decreasing risk in RR.

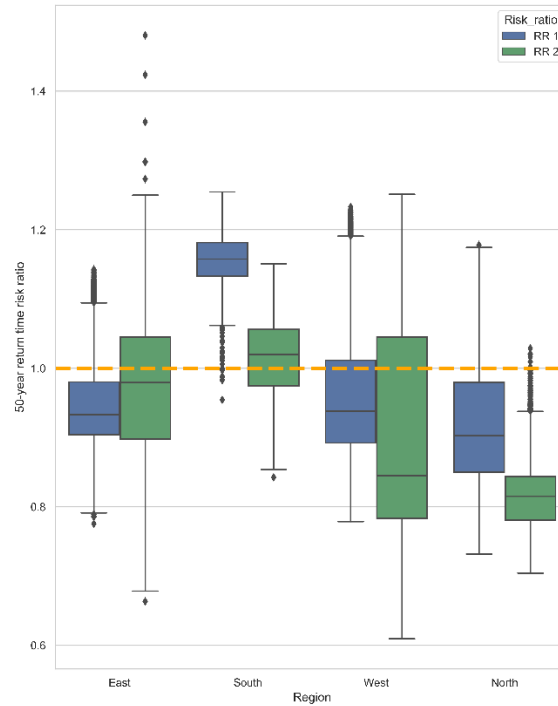


Figure 6.7. Box plot for RR of wind gust (m/s) corresponding to 50 year return period (U_{50}). The four panels are regions East, South, West, and North. RR1: is 2021-2040 / 1981-2000 (blue), RR2: is 2061-2080 / 1981-2000 (green). The horizontal orange line refers to RR= 1 (no change in exceeding a threshold). The box holds the interquartile ranges (IQR), the midline represents the median. The thin vertical black line represents the rest of the distribution, except for points determined to be “outliers”. The whiskers show the maximum and minimum values. The points beyond the thin vertical lines are outliers.

6.4.2 The 35 m/s threshold

(a) The 35 m/s RC: We investigated the cut-out wind gust that impacts the wind turbine production in two future periods by calculating the return period corresponding to 35 m/s in future periods compared to the historical period. The RC estimates for return period corresponding to 35 m/s are shown in Figure 6.8 (a) 2021-2040 relative to 1981-2000, (b) 2061-2080 relative to 1981-2000, and (c) 2061-2080 relative to 2021-2040. In Figure 6.8, a positive relative difference (red shades) indicates that the return period corresponding to 35 m/s is larger in the future period compared to the historical period, meaning a decreasing risk for siting OWF in the location. At the same time, negative RC values (blue shades) show that the return period in future periods is smaller than the baseline period, which indicates increased risk. In Figure 6.8 (a), most of the decreasing risk areas for siting OWF lay above latitude 54° N and decrease

in return period up to 23% is in the south of the EEZ. Figure 6.8 (b) show more decreasing risk locations above latitude 57°N (~ 5% - 47% increase in return period). In Figure 6.8 (c), the East region shows a large area with a decrease in return period up to 23%.

Table 6.2 (row 2: 35 m/s) summarises the RC results in Figure 6.8. For 2021-2040 relative to 1981-2000 and 2061-2080 relative to 1981-2000, the North region is the most favourable, with 10.4% and 0.1% of locations having a less frequent return period in the future, respectively. Moreover, for the same two RC calculations, the South region has more areas with an increased risk for more frequent 35 m/s wind gusts. In 2061-2080 relative to 2021-2040, the South and the East regions have the least and the greatest number of locations with more frequent 35 m/s, respectively.

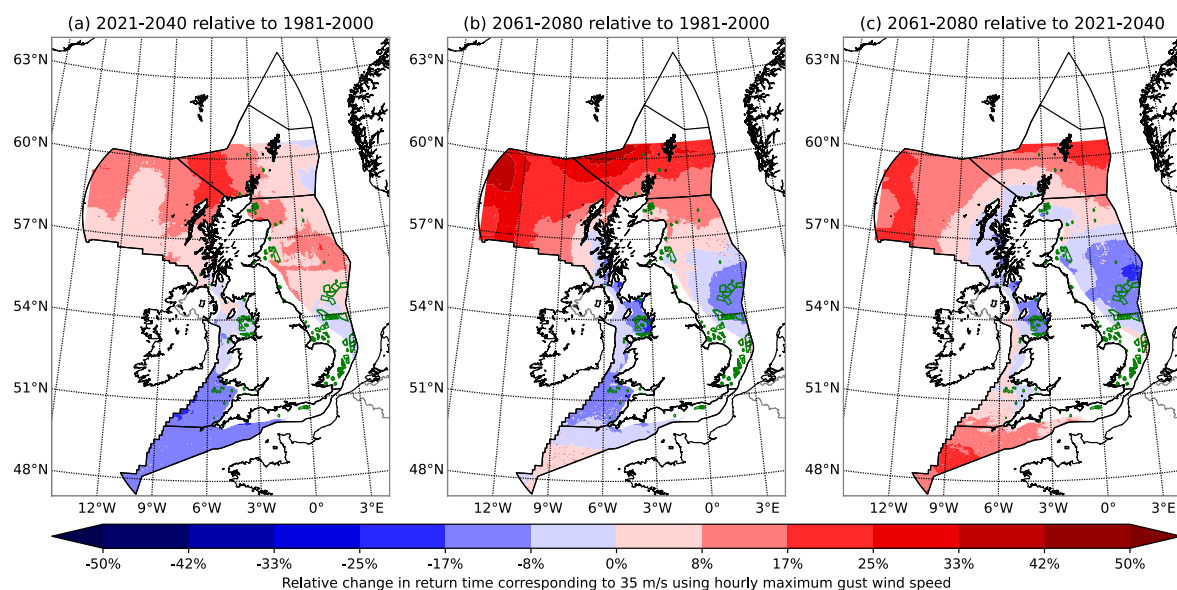


Figure 6.8. RC using 35m/s wind gust return period. (a) 2021-2040 relative to 1981-2000, (b) 2061 2080 relative to 1981-2000, and (c) 2061-2080 relative to 2021-2040. The actions with a return period greater than 100 years have been masked. Black outer boundaries represent the EEZ, and black internal boundaries are the four regions. The green lines represent the fixed bottom wind farms and floating wind farms in UK offshore area. The data include all pre-planning, planning, construction, and operational phases.

Figure 6.9 shows the statistics of the 35 m/s return period compared to the four regions. In the East region, the 2061-2080 period has a decreasing median compared to the other two periods, indicating an increased risk for more frequent 35 m/s wind gusts. Moreover, the 2021-2040 period in the West region has the lowest median compared to the other two periods. Same as the conclusion of the U_{50} threshold, see Figure 6.5, the West and North regions have the lowest return period range for the three periods (35 m/s is more likely to occur). Simultaneously, the two future periods in the West and North regions consistently increase the median, indicating less frequent 35 m/s compared to the historical period.

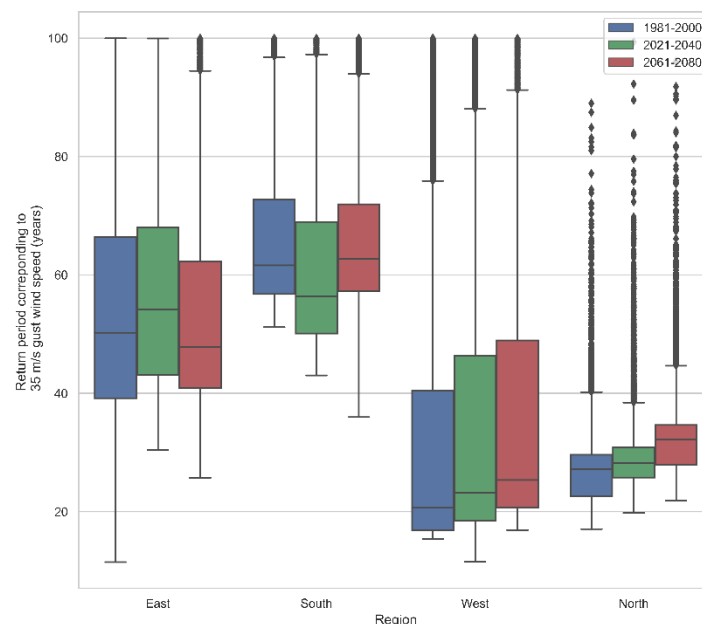


Figure 6.9. Box plot for return period corresponding to 35m/s (years). The four panels are regions East, South, West, and North. (1981-2000 (blue), 2021-2040 (green), 2061-2080 (red)). The box holds the interquartile ranges (IQR), the midline represents the median. The thin vertical black line represents the rest of the distribution, except for points determined to be “outliers”. The whiskers show the maximum and minimum values. The points beyond the thin vertical lines are outliers.

In general, the South region has an increased risk of more intense (U_{50}) and frequent (35 m/s) wind gusts in the 2021-2040 and 2061-2080 periods. The North region has a decreased risk for more intense and frequent wind gusts in the 2061-2080 periods. For 2061-2080 relative

to 2021-2040, the East and South regions have the most and the least risk for more intense and frequent wind gusts, respectively.

(b) The 35 m/s RR: The probability of meeting or exceeding the 35 m/s wind gust threshold in future periods is calculated. $RR > 1$ indicates exceeding the 35 m/s threshold has become more common in the future period. Figure 6.10 (a) and (b) show the spatial calculation for RR1 and RR2. In Figure 6.10, red shades indicate a high 35 m/s exceeding. Blue shades indicate lower 35 m/s exceeding. Locations above latitude 54° N in the 2021-2040 period have $RR < 1$, and in 2041-2080, locations above 57° N also have $RR < 1$ (indicating that exceeding 35 m/s is low). The statistical representation for the spatial calculations is in Figure 6.11. The South region is the only region with two future periods with a RR region median >1 , indicating an increased risk of more than 35 m/s wind gust in the region.

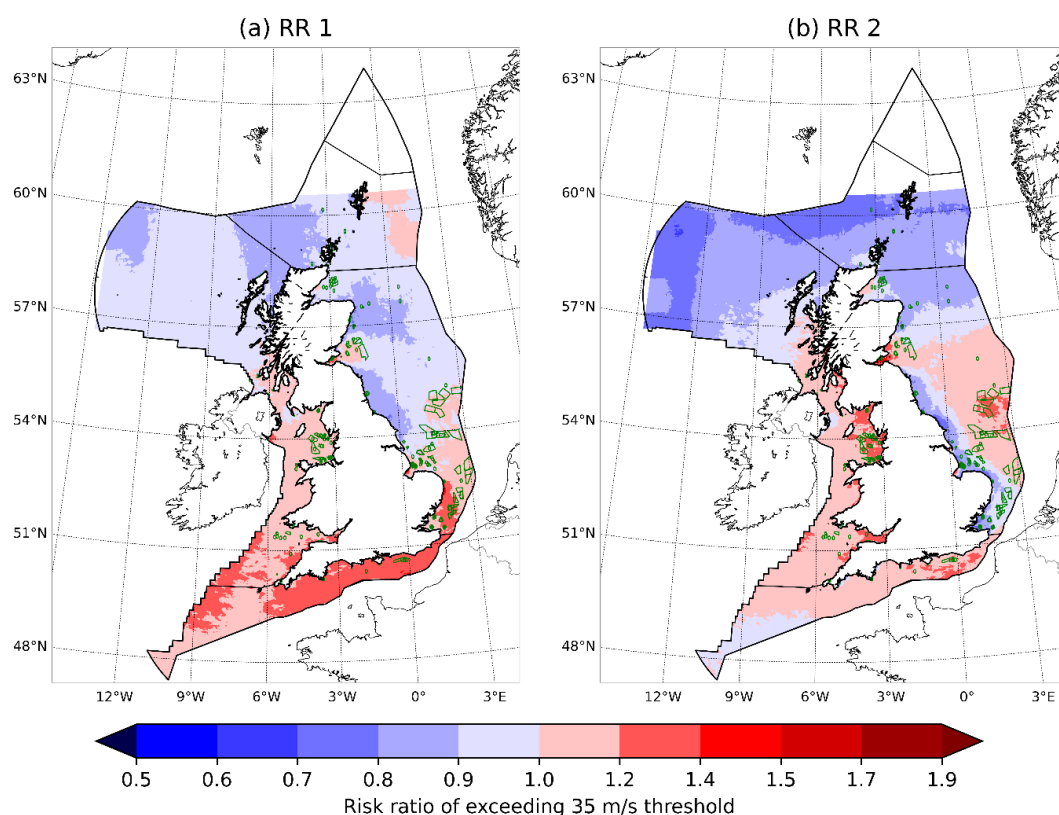


Figure 6.10. RR of 35m/s wind gust. (a) 2021-2040 against 1981-2000, (b) 2061-2080 against 1981-2000. The red shades represent the increased risk in RR, and the blue shades represent the decreasing risk in RR.

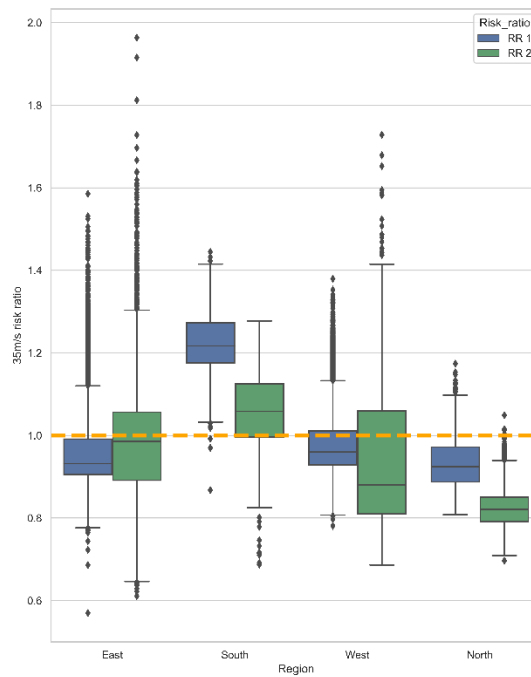


Figure 6.11. Box plot for RR of 35 m/s wind gust. The four panels are regions East, South, West, and North. RR1: is 2021-2040 / 1981-2000 (blue), RR2: is 2061-2080 / 1981-2000 (green). The horizontal orange line refers to RR= 1 (no change in exceeding a threshold). The box holds the interquartile ranges (IQR), the midline represents the median. The thin vertical black line represents the rest of the distribution, except for points determined to be “outliers”. The whiskers show the maximum and minimum values. The points beyond the thin vertical lines are outliers.

6.5 Extreme high wind speed conclusion remarks

Mitigating possible future weather risks specifically HWE risks that OWF will be exposed to can lead to longer wind turbine lifetime and sustained investment in wind energy. To quantify the future change in risk of no-operational (which can influence the operational cost) and structure loading on OWT (which can cause structural damage to the wind turbine), we investigate the future change in climate change signals using the wind turbine manufacturer threshold for stopping operational (35 m/s cut-out wind gusts) and extreme loading (U_{50}), respectively. The 35 m/s cut-out wind speed aligns with the technical specifications of many modern offshore wind turbines, which are designed to automatically shut down operations when wind speeds exceed this threshold. This is a safety mechanism aimed at preventing damage to turbine components, such as blades, rotors, and supporting structures,

when exposed to excessively high winds. By using this cut-out threshold, the model can accurately simulate scenarios where wind turbines would cease generating power to avoid damage, thereby quantifying the impact of extreme wind events on operational downtime and associated costs. Moreover, the choice of 35 m/s as a threshold reflects the balance between maximizing turbine operation time and minimizing the risk of damage. Offshore wind farms are designed to operate efficiently under a wide range of wind conditions, but extreme wind events above this threshold introduce significant risks to both operational costs and turbine integrity. By setting this threshold in the model, suitable locations for offshore wind farms can be identified based on both their energy generation potential and their ability to minimize exposure to high-risk wind conditions. Analysis showed that Beta distribution most closely represents the hourly wind gust data within UK EEZ. The return period calculations are used to get the return period corresponding to the 35 m/s threshold and the wind gust threshold corresponding to U_{50} . The chapter analysis has been done in terms of a comparison between the four regions, East, South, West, and North. For U_{50} and 35 m/s, we analysed the RC and RR for the four regions using the three different time points.

Using U_{50} , the RC determined sites with the most negligible and largest effect from climate change for future OWF repowering (The recommendation for repowering is based on the direction of change (whether an increase or decrease) between the baseline and future scenarios. The decision is made without considering the specific magnitude of the change but rather based on whether particular factors are expected to improve or decline). Generally, the RC calculations indicate the increased risk in certain locations compared to what it has experienced in the historical period. Wind farms installed in certain locations are designed to engineering specifications suitable for historical weather conditions. Adding the RC calculations gives an intuition as to what change this turbine can face in the future by so planning for future engineering design.

The East and North regions show the least negative impact on installing future OWF in 2021-2040 and 2061-2080, respectively. The South is the least favourable in both future periods. These results need to be taken into consideration for the current OWF installed projects as they indicate the expected U_{50} change in the future compared to what they already experienced in 1981-2000. Regarding reaching the best siting among the four regions, it must be noted that although the South region has the majority of locations with ~10% increased wind gusts in the two future periods, in general, it has the lowest range of wind gust values compared to the other areas (from 29 m/s to 37 m/s). Moreover, although the relative change shows a favourable indication in the North region as the wind gust decreased in most locations in 2061-2080 compared to the baseline, it must be noted that the range of wind gust values for the majority of the locations in the North region has a higher value than East and South regions, see Figure 6.5.

Using 35 m/s cut out wind gust, we aim to quantify the effect that future 35 m/s wind gusts could have on wind turbine operation in a specific location, thereby informing the optimal siting of future OWF. We have demonstrated the RC of 35 m/s return period and risk of exceeding 35 m/s over the four regions for two future time windows. The South is the least favourable in both future periods. The North areas showed the most favourable indicators for decreasing future climate impact on the existing wind farms in the 2021- 2040 and 2041-2080 periods. This is because the two future periods indicate a lower frequency in occurring 35 m/s winds compared to the baseline period. However, when considering all four regions, it is essential to recognise that although the future climate change signals predict a lower risk in the North, both the North and West regions exhibit a lower range of return period compared to the other regions in all three periods (35 m/s is more likely to occur compared to the other regions). This implies a higher risk of more frequent 35 m/s winds occurring in these regions than in the other regions. Moreover, although the South region has the majority of locations with more

frequent occurrence of 35 m/s in the two future periods, it has the highest range of return period values compared to the other regions (from 35 to 100 years), indicating a less risk for OWF installed in the region. On the other hand, we found similarity in undesirable future climate change signals in siting locations for both the return of 35 m/s and the U_{50} in the South sites of the UK offshore area between latitude 48° N and 52° N.

The inclusion of significant wave height is crucial for comprehensive climate impact studies, as it can significantly influence marine and coastal environments similar to extreme wind speeds. Despite its importance, significant wave height was excluded from this research due to the substantial computational resources required to process the new dataset. This research already involves an extensive analysis utilising hourly mean wind speed, daily mean wind speed, hourly maximum wind gust, daily temperature, and daily pressure data. Future work will aim to integrate significant wave height, acknowledging its potential impact. Section 8.2, "Future Directions," discusses considerations for this integration.

Chapter 7 Offshore wind farms future siting model

7.1 Overview

This chapter aims to reduce wind power variability by implementing strategic wind power capacity distribution in the UK exclusive economic zone (EEZ) in the future. Several models in the literature have been introduced to investigate OWF siting by choosing optimal areas for multivariate activities and facilities [5], [38], [121], [138]–[141]. These models use multi-criteria decision analysis to estimate the best OWF locations, considering criteria such as wind speed, water depth, distance to shoreline, and the grid to select the most suitable location for siting OWFs. In contrast, few studies have considered coupling future climate change and extreme weather event occurrence and severity with the future planning of wind energy from a spatial perspective [35], [13], [31]–[34]. Therefore, this chapter seeks to site OWFs by incorporating the key factors highlighted in the previous chapters that target avoiding exposing the wind turbine to future weather hazards, such as lower production and acceleration to turbine rotor (sudden increases in gusts cause rapid acceleration of the rotor, which the control systems must quickly respond to in order to maintain safe operation, and can push the turbine to its operational limits), and damage to wind turbine structure caused by high wind speed, along with economic criteria. Three Multi-criteria decision analysis (MCDA) methods (Vikor, Topsis, and Cocos) were used to obtain a unified decision for OWF planning to achieve the best solution.

The chapter is organised as follows: Section 7.2 provides the background for the OWF siting model. Section 7.3 and 7.4 presents the ten criteria chosen for the siting model from the

analysis of the previous chapters and their results on the three climate periods, respectively. Section 7.5 show the weights considered for the ten factors. In section 7.6, the three MCDAs used in this thesis are illustrated. Sections 7.7 and 7.8 apply these three MCDAs on all UK EEZ grid cells for the baseline period and tests the correlation between these methods. Finally, the ranking results for the three climate periods are compared in section 7.9.

7.2 Background

Quantitative methods can handle sophisticated system conditions. MCDA is a procedure that aims to define how the attributes are processed to decide on which choice is the best among all possible alternatives to meets the objectives [138]. MCDA is the most effective and widely used tool in spatial planning and siting of wind farms as multiple technical, economic, and environmental criteria need to be considered and prioritised for siting wind farms [142], [138], [25]. Multiple MCDA methods have been introduced in the literature, each of them has its advantages and disadvantages [143]–[148]. There is no specific rule to decide the most appropriate method to solve a problem [149], and because of the large number of MCDA methods, the selection is highly dependent on the context. Also, defining the problem parameters and objectives can help in the selection of the most suitable method for the spatial problem. Decision-makers should select among the different techniques the methods that best fit their decisional context. For this reason, applying different MCDA methods to the same problem can help to improve the quality of decision-making [149]. This chapter will use three MCDA methods to solve the OWF siting problem, such as Vikor [144], Combined Compromise Solution (Cocoso) [145], and Technique for Order Preferences by Similarity to Ideal Solution (Topsis) [150]. The selection of these three MCDA methods was by comparing the results of six wide usage MCDA methods in spatial planning problems (Vikor, Topsis, Cocoso, Premethee (Preference Ranking Organisation Method for Enrichment of Evaluations)

II [146], Edas (Evaluation based on Distance from Average Solution) [151], and Marcos (Measurement of alternatives and ranking according to Compromise solution) [148]). The comparison gives a broad understanding of the problem parameters and helps to decide if an alternative methodology could be more suitable for future, more complex, siting wind farm decisions. Using Pearson [152] and Kendell [153] correlation tests, Vikor, Topsis, and Cocosco exhibited the best correlations across all other methods. Section 7.6 gives more details about these three MCDA methods. Figure 7.1 provides an overview of the methodology of using MCDA. The framework in Figure 7.1 is summarised in five stages:

- Stage 1 represents the process of selecting the ten factors. Detailed description is in section 7.3.
- Stage 2 shows the use of these factors in the three climate periods. Detailed description is in section 7.4.
- Stage 3 means performing a survey using the opinion of ten experts to weigh the ten factors, followed by normalise the weighting. Detailed description is in section 7.5.
- Stage 4 represents using the three MCDA methods and testing the correlation between the methods. Detailed description is in sections 7.7 and 7.8, respectively.
- Stage 5 shows results from the framework that presents the differences between ranking the three climate models. Detailed description is in section 7.9.

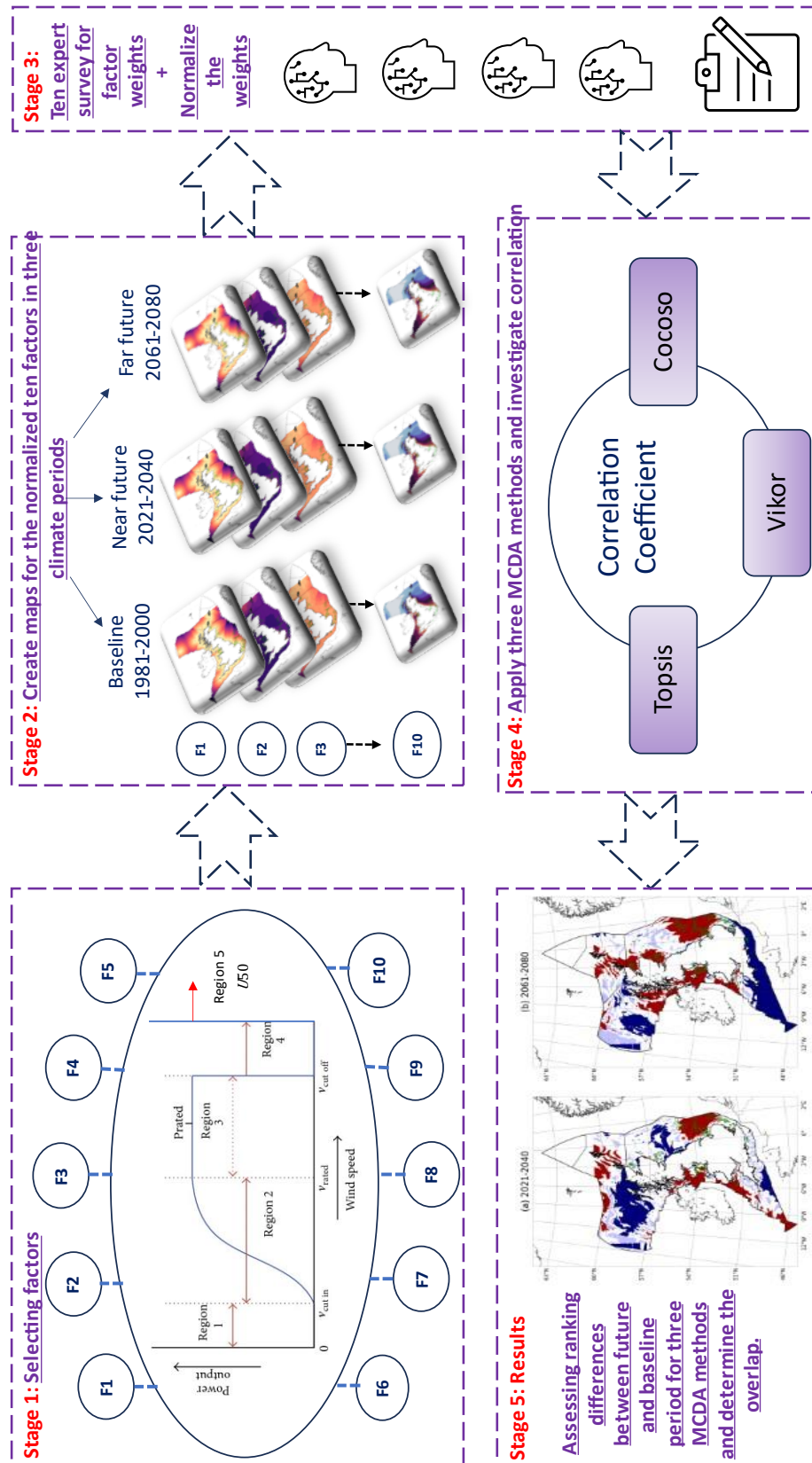


Figure 7.1. Overview of the methodology procedures.

7.3 Stage 1 - Criteria considered in the siting model.

Chapter 4 to chapter 6 covers the impacts of climate change on the UK offshore areas, considering future variations and stability in wind energy; the future change in extreme LWE; and the future change in maximum wind gust with implications for both generation (cut-out wind speed) and extreme loading on the wind turbine structure. This chapter utilises eight factors based on the previous analysis of extreme HWE, LWE, and wind production, as seen in Table 2.1 (F1 – F8), to set the preferred locations for future siting. The factors are criteria that suppress or enhance the suitability of location for OWF development.

Stakeholder and expert opinion are used to estimate weightings of the chosen factors. Key stakeholders/experts have been involved in the entire decision-making process. Three MCDA methods will be used to compare their correlated preference locations. The MCDA methods are Vikor [144], Topsis [143], and Cocosco [145]. As a result, for each of the three chosen MCDA methods, we can allocate locations where wind speed has the best potential to produce power and is more resilient to projected changes in future extreme wind speed.

The most important criterion when choosing a new site for energy production is the resources for that platform. The wind resource is the baseline for economic, technical, and political developments of wind energy applications. In this research, we are not just considering wind resourcing in future siting but also considering economic factors. Wind turbine costs often restrict the expansion of wind turbine installation. This is not just affected by wind turbines being exposed to more frequent EWEs, but also it is governed by wind turbine location and installation. Therefore, our analysis will consider the OWF distance to shore and the water depth for the installation sites. [154]. The two economic factors included in the study are as follows:

(a) F9: Water depth, see Figure 7.2 (a). Logistic costs increase proportionally with the increase in water depth, and more expensive foundations are required [138], [155], [156]. Currently, in shallow waters, the most employed foundations for depths less than 30 m are monopiles [5]; jacket foundations are used for water in depths between 30 to 60 m [5]; semi-submersible [157] and Tension leg platform (TLP) [157] can be installed in-depth > 60 m, spar structures are used when the bathymetry depth is greater than 120 m [158].

(b) F10: Distance to coast, see Figure 7.2 (b). DC is closely interconnected with conversion efficiency, cost reduction, and the establishment of electricity interconnections. Increasing the length of underwater transmission power cables that connect the electrical grid with OWF can lead to higher transmission losses. High-voltage alternating current (HVAC) transmission cables are considered cheaper for around 600 km. Beyond that distance, the recommendation is to use the high-voltage direct current (HVDC) for offshore transmission [154], [155], [138]. For floating offshore wind farm projects, HVDC is recommended to overcome the electrical losses caused by the export cables in a long grid connection [159].

The proximity to the nearest substation, which likely influences cable costs, differs from the proximity to the nearest port, relevant for installation and maintenance operations. In this research, the distance to the coastline was used as a general proxy for distances to substations, ports, and the electricity grid. This approach simplifies the analysis by consolidating multiple logistical factors into a single metric.

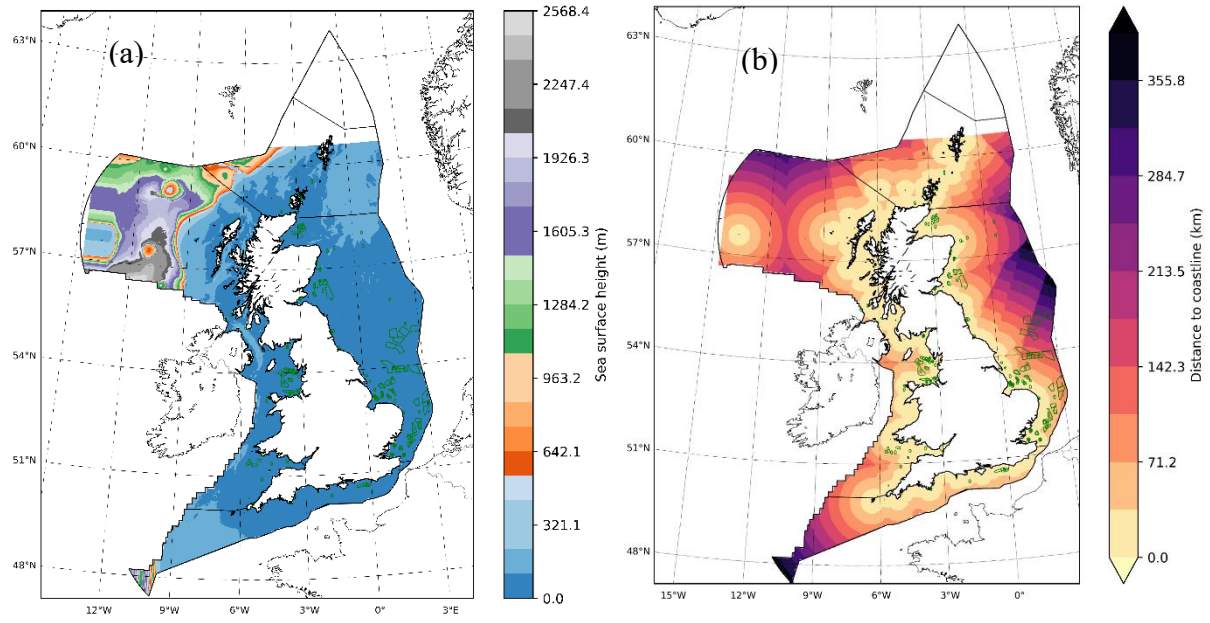


Figure 7.2. (a) Bathymetry in (m) [171], (b) Distance to shore in (km).

7.4 Stage 2 - Criteria normalisation in three climate periods

All criteria should be normalised to transform the different units and magnitudes involved to a similar scale [38], [160]. The Min-Max normalisation method described below is used to normalise criteria considered in this study such that normalised values fall between 0 and 1. The indices are also reversed if required so that in all cases the optimal value is 1, and the worst value is 0.

In the Min-Max normalisation method a decision matrix X with n alternatives and m criteria (equation (7.1)) can be normalised in two ways depending on whether high or low values of the criteria represent optimal conditions.

$$X = (x_{ij})_{n \times m} \quad (7.1)$$

To normalise criteria where high values represent optimal conditions, such as WPD, CF, Low wind, and 35m/s, equation (7.2) is used.

$$r_{ij} = \frac{x_{ij} - \min_j(x_{ij})}{\max_j(x_{ij}) - \min_j(x_{ij})} \quad (7.2)$$

To normalise criteria where low values represent optimal conditions, such as COV, MV, SV, 50YEAR, DC, and WD, equation (7.3) is used.

$$r_{ij} = \frac{\max_j(x_{ij}) - x_{ij}}{\max_j(x_{ij}) - \min_j(x_{ij})} \quad (7.3)$$

In both cases the results for r_{ij} will be a range of values between 0 and 1, where 1 represents the most favourable conditions and 0 the least favourable.

Figure 7.3 shows the normalised WPD, CF, COV, and MV, and Figure 7.4 shows the normalised SV, 35m/s, 50YEAR, and Low wind criteria (that have been discussed in previous chapters) in 1981-2000, 2021-2040, and 2061-2080.

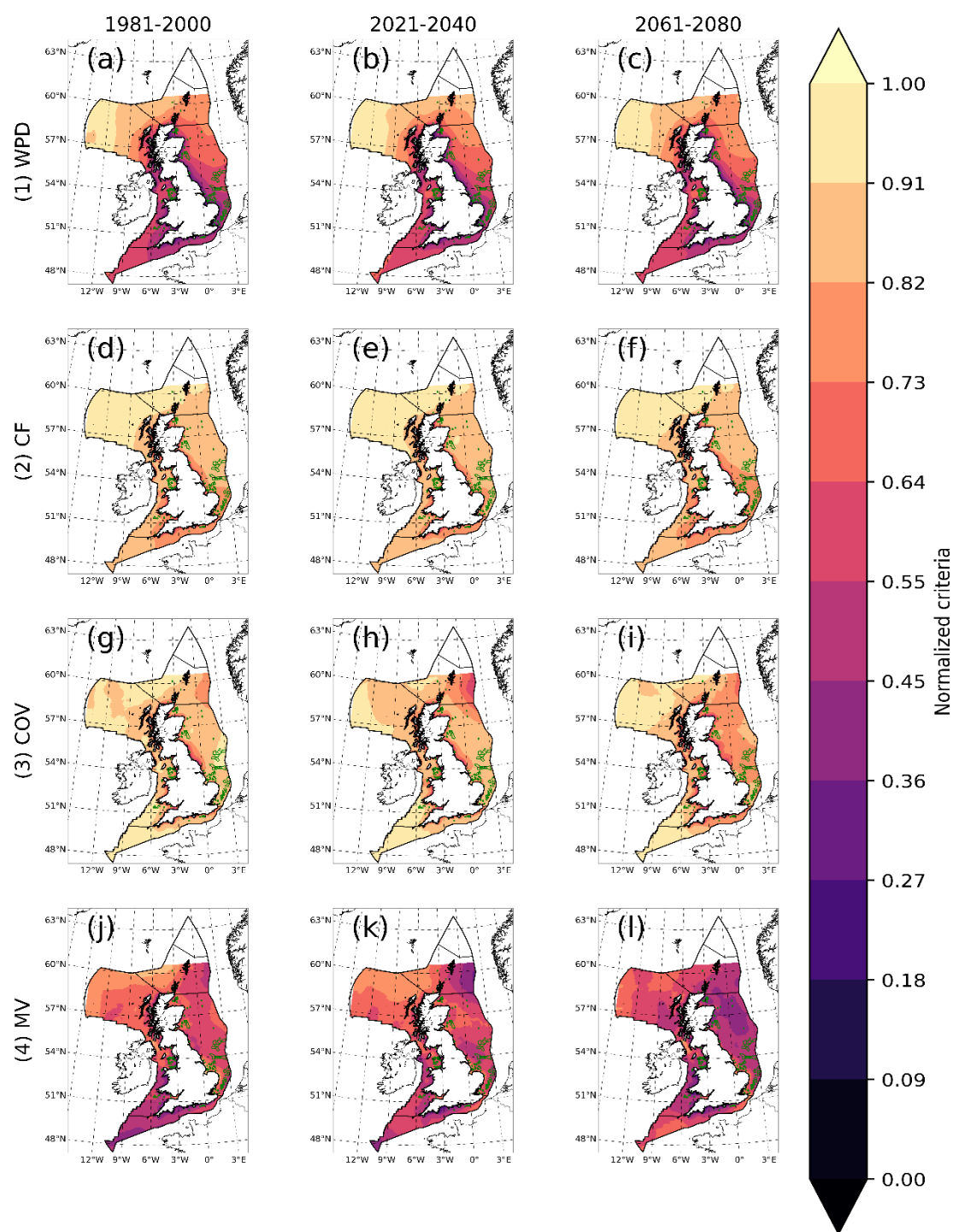


Figure 7.3. Spatial map representing the normalised criteria in baseline and two future periods for the first four criteria, rows from 1 to 4 represent: WPD, CF, COV, and MV. Columns from left to right shows 1981-2000, 2021-2040, and 2061-2080.

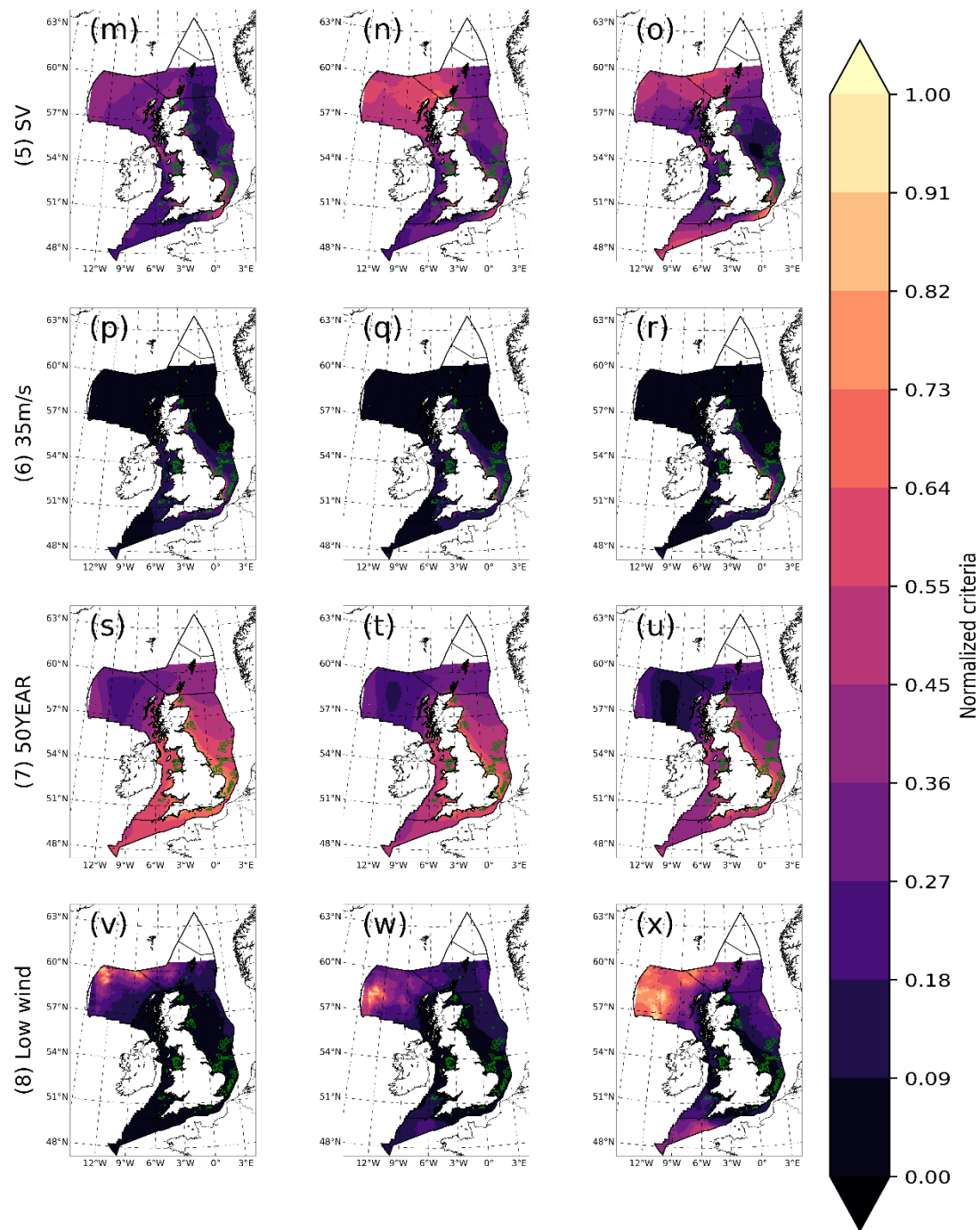


Figure 7.4. Spatial map representing the normalised criteria in baseline and two future periods for the second four criteria, rows from 1 to 4 represent: SV, 35m/s, 50YEAR, and Low wind. Columns from left to right shows 1981-2000, 2021-2040, and 2061-2080.

7.5 Stage 3 - Weighting the siting model criteria.

To determine the relative importance of each of the ten criteria, we asked 20 candidates to participate in a survey. The survey participants are identified by their history of publication in the wind energy field (academia) or being an expert in the wind energy industry due to their position within relevant organisations (Wind Turbine manufacturers, Wind Farm operators and energy investment professionals) (industry). No particular length of experience was required. We emailed the participant, including the link to the Jisc application (survey platform), which has the consent form and the survey. Participants will be directed to the survey if they accept the consent form. Along with approaching 20 by email candidates, the thesis work was presented at the University of Bristol, where we also showed a slide in the presentation with a QR code that gives access to the survey. The conference attendees were academics from different universities and stakeholders from the Crown estate. Overall, ten participants have responded by providing weighting that reflects the priority for each of the ten criteria in siting OWF. The online survey anonymously collected the participants' opinions about the ten factors impacting OWF siting, which led to not knowing the percentage of academia to industry experts who participated in the survey. Each participant was asked to provide a numeric value against a fixed scale (a percentage out of 100) that weighed each of the ten factors provided in the survey. It is worth mentioning that the thesis work attracted the attention of the Crown Estate members attending the Bristol conference, and a proposal for potential collaboration was sent to them. The normalisation has been applied to map the participants weighting to the range of 0 to 1 by dividing each weight provided by a participant by the summation of the weight given for all factors, which is equal to 100. In this normalisation process, the collective sum of these factor weights equates to unity; see Table 7.1 and Figure 7.5 for the weights generated after normalisation. Figure 7.5 shows the weights provided by the 10 participants for each criterion, which gives an idea of which criteria have the highest collective weights from the 10

participants. Criteria 2 (Capacity factor) has the highest weighting, followed by Criteria 1 (WPD). On the other hand, criteria 9 (Distance to coast) and criteria 10 (Water depth) has the lowest weighting. Column PM in Table 7.1 represents the mean weights for each factor across the ten participants (P1 to P10). The sensitivity analysis for the criteria weights can be useful in measuring the intensity of the weighting on the final result of the MCDA process (overall change in ranking the alternatives). Which assesses the robustness and the stability of the ranking obtained, considering experts/stakeholders preferences. Because of the large number of data points covering the UK EEZ, it was inapplicable to apply the sensitivity computation as it needed a 10 (number of participants) ¹⁰ (number of criteria). However, a small-scale sensitivity is applied using two cases for the utilised weights: 1- normalised weights from the AHP method (see **Appendix B**) and 2- equal weights for the ten participants (see **Appendix C**). In **Appendix B**, the AHP method has been used as an alternative way to normalise the factors. Also, the final results of ranking with the AHP weighting are shown in **Appendix B**. In **Appendix C**, equal weights are assigned to the ten participants to show the ranking of the EEZ locations independent from factor preferences. Vikor was not used in ranking using equal weighting analysis as it showed a low correlation with Topsis and COCOS. For both the AHP weights and the equal weights analysis, the results are very similar to those in sections 7.7 and 7.9.

Table 7.1. Normalised weights for the 10 participants. PM is the mean of all weight. Pink and blue highlights indicate each participant's maximum and minimum weighting values, respectively.

Participants	Weights										
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	PM
(1) WPD	0	0.308	0.05	0.13	0.05	0.155	0.11	0.2	0.1	0.185	0.1288
(2) CF	0.4	0.308	0.05	0.13	0.4	0.155	0.11	0.2	0.15	0.285	0.2188
(3) COV	0.1	0.208	0.05	0.12	0.025	0.055	0.09	0.15	0.15	0.035	0.0983
(4) MV	0	0.018	0.15	0.12	0.025	0.055	0.13	0.1	0.15	0.035	0.0783
(5) SV	0.1	0.038	0.25	0.12	0.2	0.055	0.16	0.1	0.05	0.085	0.1158
(6) 35m/s	0	0.018	0.1	0.14	0.1	0.055	0.06	0.1	0.05	0.135	0.0758
(7) 50YEAR	0.1	0.018	0.15	0.1	0.05	0.105	0.11	0.05	0.1	0.085	0.0868
(8) low wind	0.1	0.018	0.1	0.1	0.1	0.055	0.13	0	0.15	0.085	0.0838
(9) DC	0.1	0.028	0.05	0.02	0.025	0.155	0.07	0.05	0.05	0.035	0.0583
(10) WD	0.1	0.038	0.05	0.02	0.025	0.155	0.03	0.05	0.05	0.035	0.0553

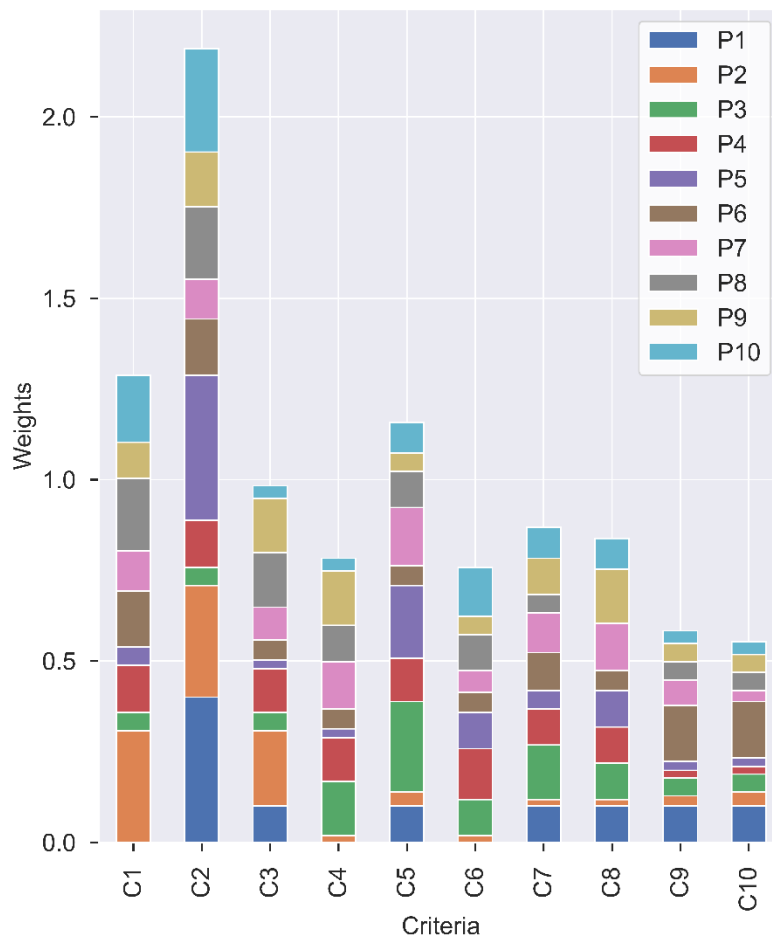


Figure 7.5. The 10 Participants (P1 to P10) weighting for each of the ten criteria (C1 to C10).

7.6 MCDA methods

MCDA is used to objectify a set of criteria in a decision-making problem for the future siting of OWFs. To achieve this, a framework was created (Figure 7.1) in which three reference sets of MCDA methods, namely Vikor [144], Cocoso [145], and Topsis [143] are compared. The analysis uses two correlation tests namely, Pearson correlation coefficients and Kendall Tau correlation, to assess the MCDA methods consistency.

7.6.1 Vikor

The Vikor method addresses discrete decision problems involving conflicting criteria [144], [161], [162]. Its main objective is to rank alternatives and identify compromise solutions for the problem at hand. This technique can be broken down into several steps following [163]:

Step 1. The decision matrix is represented with n alternatives and m criteria. f_{ij} is the value of the i th criterion for the alternative A_i as follows:

$$X = f_{ij}(A_i)_{n \times m} \quad (7.4)$$

Step 2. Define positive-ideal f_i^+ and negative-ideal f_i^- alternatives following the equations [163], where equation (7.5) is used for profit criteria and (7.6) is used for cost criteria:

$$f_j^+ = \max f_{ij}, f_j^- = \min f_{ij} \quad (7.5)$$

$$f_j^+ = \min f_{ij}, f_j^- = \max f_{ij} \quad (7.6)$$

Step 3. Determine utility S_j and regret R_j to formulate ranking measures using the equation (7.7):

$$S_j = \sum_{j=1}^m w_j (f_i^+ - f_{ij}) / (f_i^+ - f_i^-) \quad (7.7)$$

$$R_j = \max [w_j (f_i^+ - f_{ij}) / (f_i^+ - f_i^-)]$$

where w_j is the weight of the j th criterion.

Step 4. By using equation (7.8) the Vikor index (Q_i) should be evaluated.

$$Q_i = v \left[\frac{S_j^- - S^+}{S^- - S^+} \right] + (1 - v) \left[\frac{R_j^- - R^+}{R^- - R^+} \right] \quad (7.8)$$

Where,

$$S^+ = \min_i S_j, S^- = \max_i S_j$$

$$R^+ = \min_i R_j, R^- = \max_i R_j$$

The parameter v determines the relative importance to find a compromise solution. . $v = 1$ means the decision-maker prioritises the strategy that considers the best performance in at least one criterion. $v = 0$ indicates that the decision-maker is more focused on achieving a compromise solution that is acceptable for the majority. This research used $v=0.5$ which represents a balanced approach between $v = 1$ and $v = 0$.

Step 5. Rank the alternatives, sorting by the values Q , values closer to zero mean a better alternative. In this way we obtained the final rank.

7.6.2 Topsis

The Topsis method is similar to VIKOR method, both are based on determining the distance between objects and the ideal and anti-ideal solutions [143], [162]. However, the two methods differ in their operational approach and how they consider the concept of proximity to the ideal solutions. The Topsis method results in a synthetic coefficient that ranks the objects being studied. The object with the shortest distance from the ideal solution and the greatest distance from the anti-ideal solution is considered the best. In summary, the formal description of the Topsis method is described below following [163]:

Step 1. Create a weighted decision matrix using the normalised criteria from equations (7.2) and (7.3).

$$v_{ij} = w_j r_{ij} \quad (7.9)$$

where v_{ij} is the value of the weighted normalised decision matrix and w_j is the weight for j criterion. r_{ij} is the normalised value.

Step 3. Determine maximum and the minimum value for each criterion which represent the positive ideal solution and the negative ideal solution vectors according to the following:

$$v_j^+ = \{v_1^+, v_2^+, \dots, v_m^+\} = \{\max_j(v_{ij})\} \quad (7.10)$$

$$v_j^- = \{v_1^-, v_2^-, \dots, v_m^-\} = \{\min_j(v_{ij})\}$$

Step 4. Calculate the separation measure from the maximum and minimum criteria for each alternative according to the following formula.

$$\begin{aligned} S_i^+ &= \sqrt{\sum_{j=1}^m (v_j^+ - v_{ij})^2} \\ S_i^- &= \sqrt{\sum_{j=1}^m (v_j^- - v_{ij})^2} \end{aligned} \quad (7.11)$$

Step 5. Calculate the score of each alternative based on the similarity to the worst condition using the following equation. Values closer to 1 mean a better alternative:

$$C_i = \frac{S_i^-}{S_i^- + S_i^+} \quad (7.12)$$

Step 6. Rank the alternatives by their similarity to the worst state.

7.6.3 Cocoso

Yazdani et al. [145] have introduced a novel approach, the Cocoso method, which integrates Simple Additive Weighting (SAW) and the Exponentially Weighted Product Model (EWPM). This method combines different viewpoints to resolve the conflicts often encountered in evaluation criteria. The Cocoso method offers a comprehensive perspective of potential compromise solutions that can aid decision-makers in reaching a suitable decision. The following steps illustrate the calculation procedure of the Cocoso method following [164]:

Step 1: Defining the initial decision matrix and normalise the criteria values as described before.

Step 2: Integrating the SAW and EWPM approaches by applying the following equations:

$$S_i = \sum_{j=1}^m r_{ij} w_j \quad (7.13)$$

$$P_i = \sum_{j=1}^m r_{ij}^{w_j}$$

where S_i is the sum of weight-comparable sequences and P_i is the weight-multiplied comparable sequences of the alternative i , and w_j is the weight of the criterion j .

Step 3: The Cocoso method utilises a relative performance score k_i to rank the considered alternatives, values closer to 1 mean a better alternative. $\lambda=0.5$. This score is determined by calculating three aggregate estimated results (k_{ia} , k_{ib} , and k_{ic}) and can be expressed as:

$$k_i = \frac{1}{3} (k_{ia} + k_{ib} + k_{ic}) + (k_{ia} k_{ib} k_{ic})^{\frac{1}{3}} \quad (7.14)$$

With:

$$k_{ia} = \frac{S_i + P_i}{\sum_{i=1}^n (S_i + P_i)} \quad (7.15)$$

$$k_{ib} = \frac{S_i}{\min S_i} + \frac{P_i}{\min P_i} \quad (7.16)$$

$$k_{ic} = \frac{\lambda S_i + (1 - \lambda) P_i}{\lambda \max S_i + (1 - \lambda) \max P_i} \quad (7.17)$$

7.7 Stage 4 (Part 1) - Results of utilising multi-criteria decision analysis (MCDA) techniques to integrate the future offshore wind farm siting factors.

Vikor, Cocoso, and Topsis methods were implemented to rank all cell grids in the UK EEZ. The Pymcdm package in Python has been used for the MCDA calculations [165]. The study area map is a 2.2 km equal size grid of cells with each cell being referred to as an alternative. The three MCDA methods produce a decimal number for ranking. A low value in the Vikor method indicates a more advantageous location. In contrast, a low value in Cocoso and Topsis indicates less advantageous locations. We have converted all decimal rankings to integer

ranking and considered the inverse order for Cocoso and Topsis to have a similar scale of ranking for the three MCDA methods (represented in 1 as the best rank, and the greater the rank, the less preferred the alternative), which allow comparing the results from multiple MCDA methods. The ‘rankdata ‘ from the Scipy package has been used to convert the decimal ranking to integer ranking that starts from 1, and the method used is ‘dense’, which shows the distribution of the ranking while preserving the same ranking for all locations that have the same preference. For example, the array [0.1, 0.2, 0.3, 0.2] will be converted to [1, 2, 3, 2].

In case of no multiple locations with the same preference, the maximum expected ranking is 99875, representing the number of cell grids included in the study. To simplify the description of the results, we have divided the 99875 into 12 categories, which resulted in 12 equal bins of 8323 in each category.

Figure 7.6, Figure 7.7, and Figure 7.8 show the results of the Vikor, Cocoso, and Topsis methods in the baseline period, respectively. A lower ranking indicates a more advantageous location compared to a higher ranking. In the three figures (Figure 7.6, Figure 7.7, and Figure 7.8), plots (P1 to P10) represent the ranking using the normalised weighting provided by each of the ten participants; see Table 7.1 for the normalised weighting. Also, plot PM represents the ranking using the mean of the normalised weighting from the 10 participants, and plot M(P1-P10) represents the mean of the ranking shown in plots (P1-P10).

The variation in weighting the ten criteria between the ten participants is reflected in the ranking results of the three MCDA methods, see Figure 7.6, Figure 7.7, and Figure 7.8. A trend of having more advantageous locations (low value ranking) in sites in the north and the northwest of the UK EEZ is noted across the three MCDA methods in Figure 7.6, Figure 7.7, and Figure 7.8 for all participants, except for Participants 1 (P1) there are a considerable number of sites in the northwest with a low preference for siting OWF. This trend is a result of having more desirable values in the north and the northwest of the UK EEZ for seven out of

the ten factors (C1: WPD, C2:CF, C3: COV, C4: MV, C5: SV, C8: low wind, and C9: DC). These desirable values mean a high value of return period corresponding to 4 m/s low wind speed threshold, WPD, and CF, and a low value of COV, MV, SV, and DC. Only the remaining three factors (C6: 35 m/s, C7: 50YEAR, and C10: WD) have undesirable locations north and northwest of the UK EEZ.

Moreover, for Participants 1, 3, 5, and 7, across the three MCDA methods, see Figure 7.6, Figure 7.7, and Figure 7.8 plots (P1, P3, P5, and P7), the southeast of the UK EEZ also has a preference for siting OWFs (between latitude 51°N and 54°N and intersecting with current OWF). On the other hand, in the South region, there are more unsuitable locations to site OWFs for the majority of sites in the three MCDA methods across the ten participants. According to Figure 7.17 and Figure 7.18, the southeast regions in Participants 1, 3, 5, and 7 are not recommended for future indication as an increase in ranking can be seen in two future periods.

Moreover, in the East of the UK EEZ, there is a trend of low preference for siting OWF between latitude 54°N and 57°N for the ten participants across the three MCDA methods, which extend to the north near latitude 60°N for Participants 3, 5, and 7, see Figure 7.6, Figure 7.7, and Figure 7.8 plots (P3, P5, and P7). This research will use the mean of the 10 participants rankings to capture their variability for the three MCDA methods; see Figure 7.6, Figure 7.7, and Figure 7.8 plot (M(P1-P10)). The mean of the ten participants ranking will be used to compare the baseline scenario ranking to the two future periods.

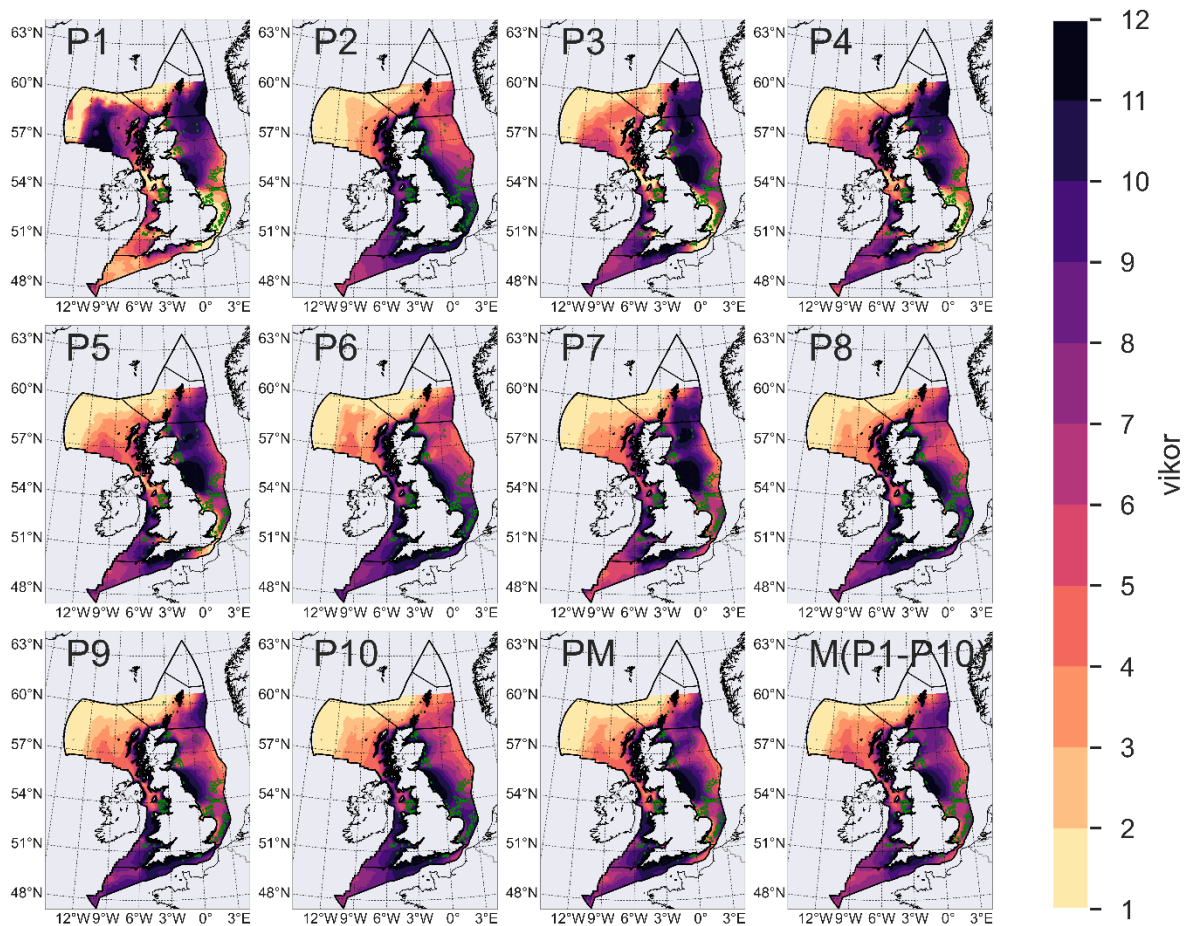


Figure 7.6. The 12 ranking categories using the Vikor method in the baseline scenario. P1 to P10 represent the ranking corresponding to the weighting of each of the 10 participants. PM is the ranking using the mean of the normalised weights for Participants P1 to P10. M(P1-P10) is the mean of the final ranking in plots P1 to P10.

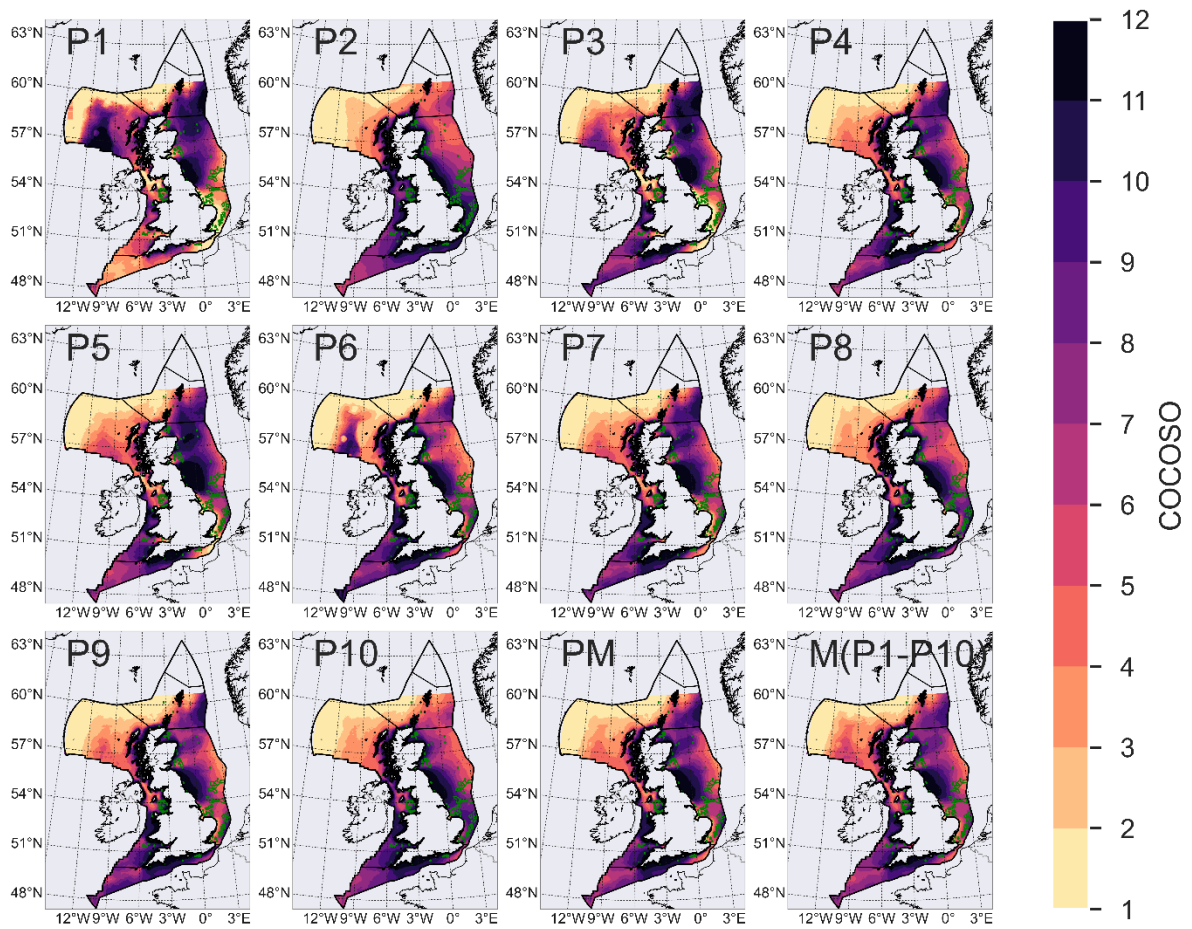


Figure 7.7. The 12 ranking categories using the Cocoso method in the baseline scenario. P1 to P10 represent the ranking corresponding to the weighting of each of the 10 participants. PM is the ranking using the mean of the normalised weights for Participants P1 to P10. M(P1-P10) is the mean of the final ranking in plots P1 to P10.

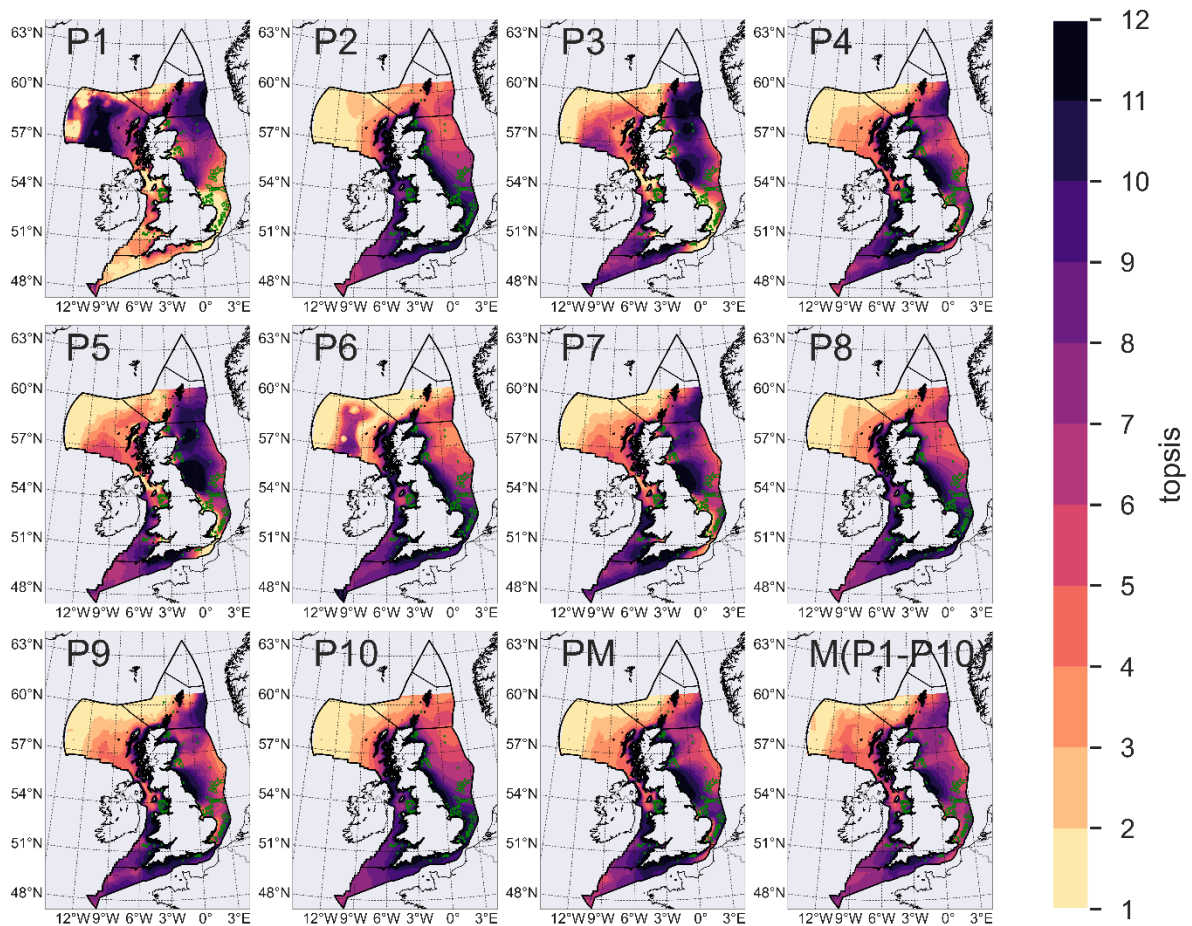


Figure 7.8. The 12 ranking categories using the Topsis method in the baseline scenario. P1 to P10 represent the ranking corresponding to the weighting of each of the 10 participants. PM is the ranking using the mean of the normalised weights for Participants P1 to P10. M(P1-P10) is the mean of the final ranking in plots P1 to P10.

The spatial variation for the baseline and two future periods can be seen in Figure 7.9. The standard deviation is up to five ranking categories. The highest variation is in the southeast of the UK between latitude 51° N and 54° N in coastline locations. This variation is more in Vikor and Topsis compared to COCOSO in the two future periods. Standard deviations in the range from one to three are dominant in four regions of the EEZ.

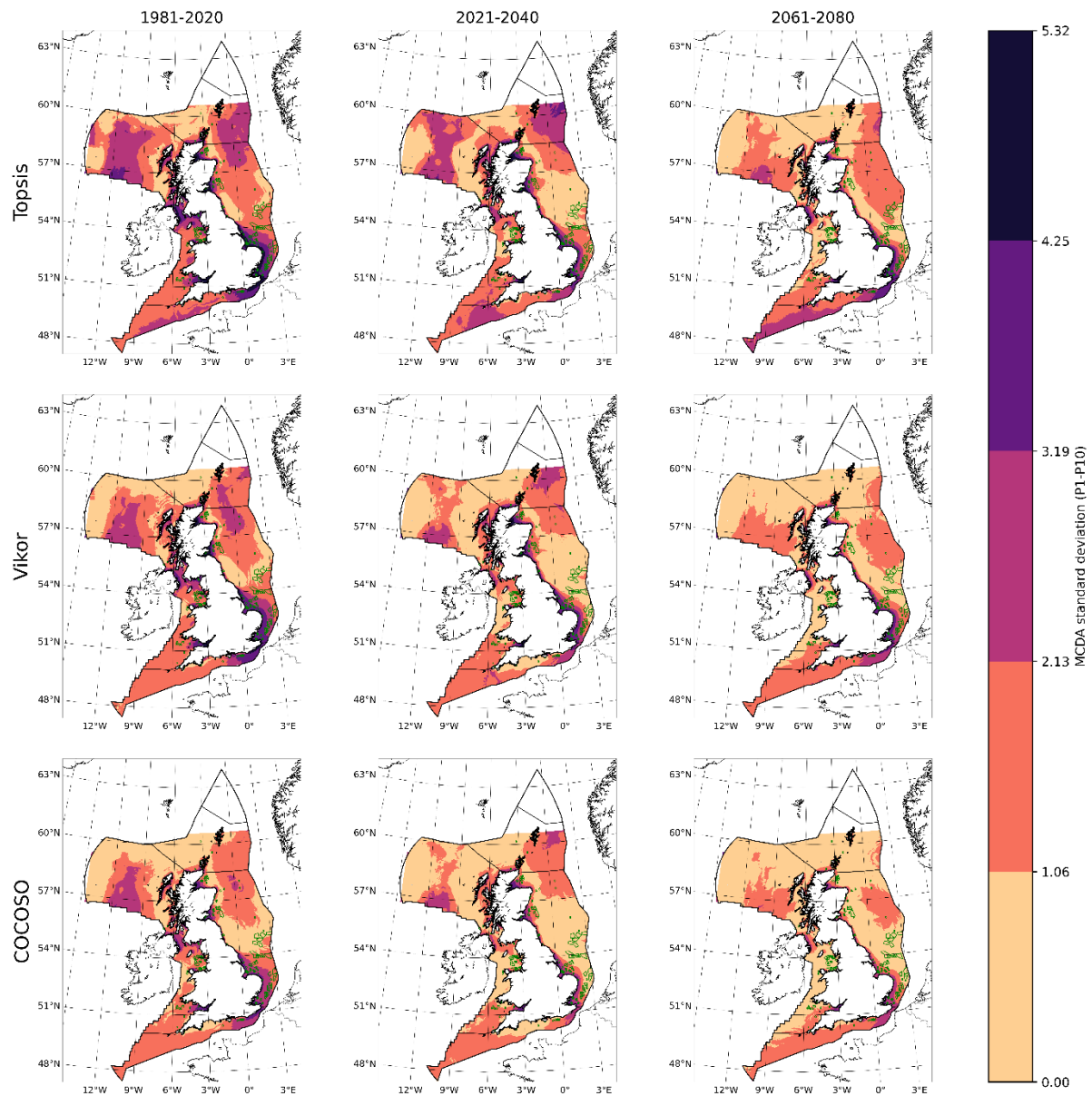


Figure 7.9. Standard deviation for the ranking obtained from the ten participants (P1-P10). Rows from 1 to 3 represent the three MCDA, Topsis, Vikor, and Cocoso, respectively, and column (a) shows the climate period 1981-2000, column (b) 2021-2040, and column (c) 2061-2080. Black outer boundaries represent the EEZ, and black internal boundaries represent four regions considered in the study. The green lines represent the fixed bottom wind farms and floating wind farms in UK offshore area. The data include all pre-planning, planning, construction, and operational phases.

Moreover, the spatial variation between the three MCDA methods for the resulted ranking from each of the ten participants weighting is shown in Figure 7.10, Figure 7.11, and Figure 7.12 for the baseline and two future periods respectively. It can be seen that the majority of the locations has a standard deviation ranging from 1 to 2, except for participant 2 (P2) where a higher

variation is seen (up to 6) in southeast locations between latitude 51°N and 54°N and in locations in the northwest of the EEZ.

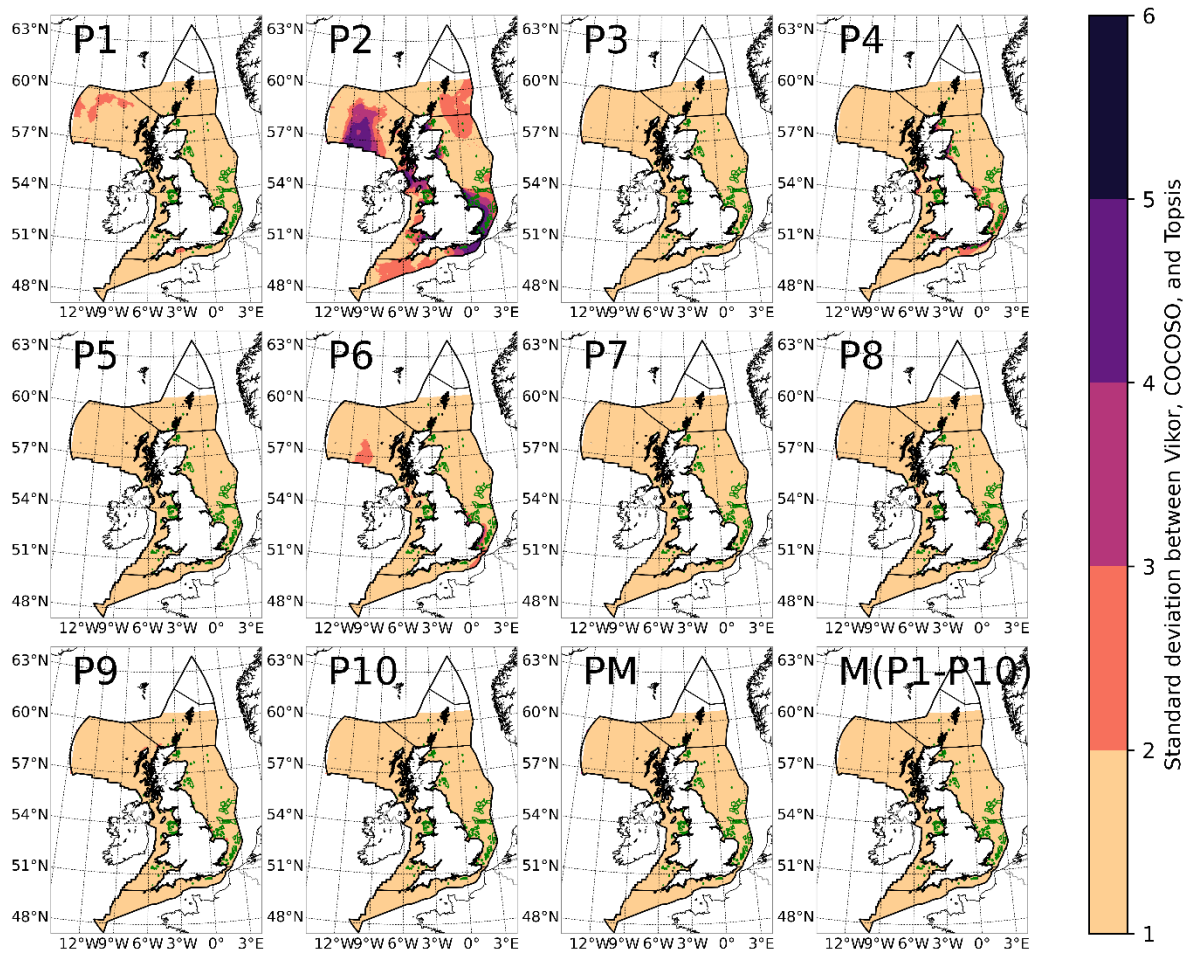


Figure 7.10. The standard deviation between vikor , COCOSO, and topsis for each of the 10 participants in the baseline scenario. P1 to P10 represent the standard deviation corresponding to the weighting of each of the 10 participants. PM is the standard deviation using the mean of the normalised weights for Participants P1 to P10. M(P1-P10) is the mean of the final ranking in plots P1 to P10.

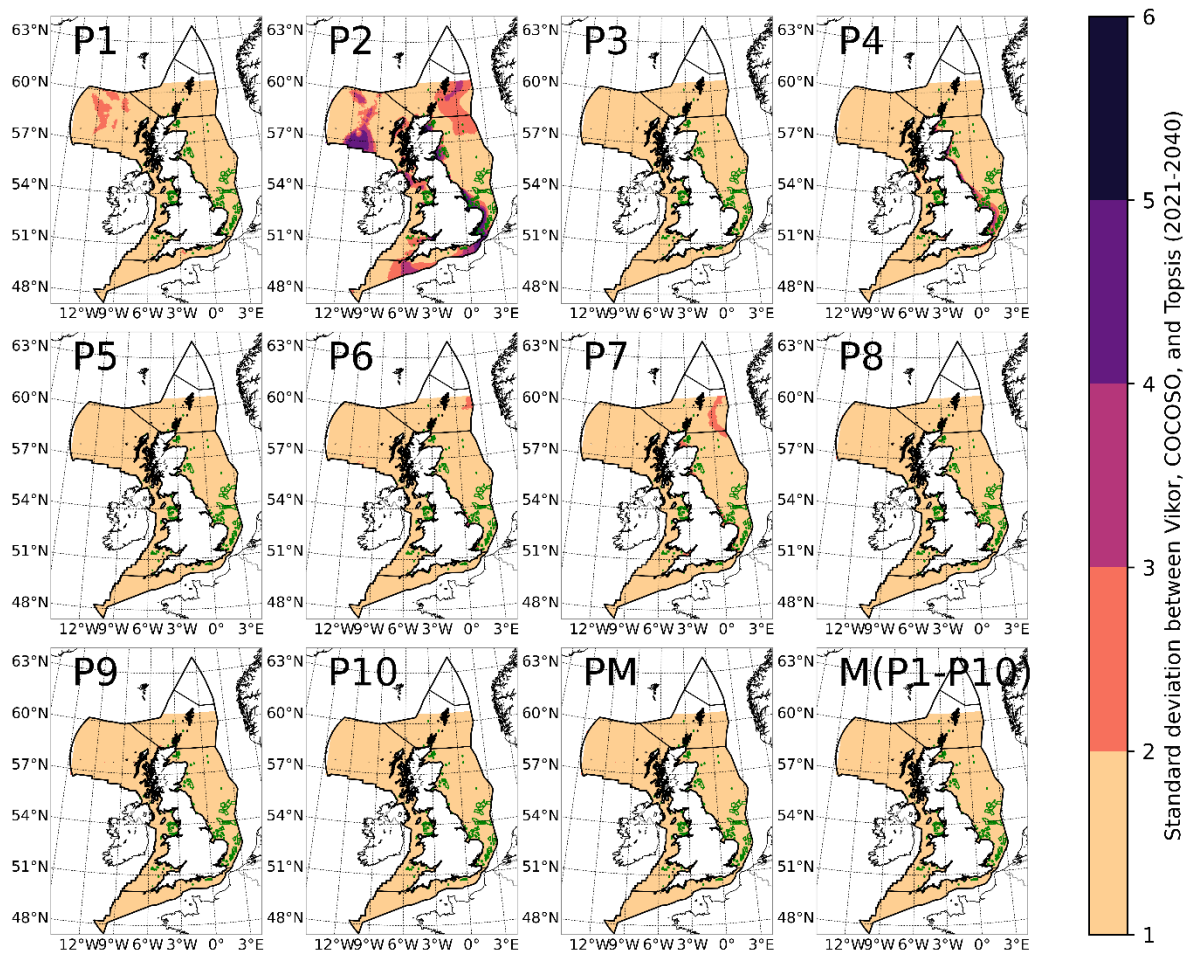


Figure 7.11. The standard deviation between vikor , COCOSO, and topsis for each of the 10 participants in the 2021-2040 scenario. P1 to P10 represent the standard deviation corresponding to the weighting of each of the 10 participants. PM is the standard deviation using the mean of the normalised weights for Participants P1 to P10. M(P1-P10) is the mean of the final ranking in plots P1 to P10.

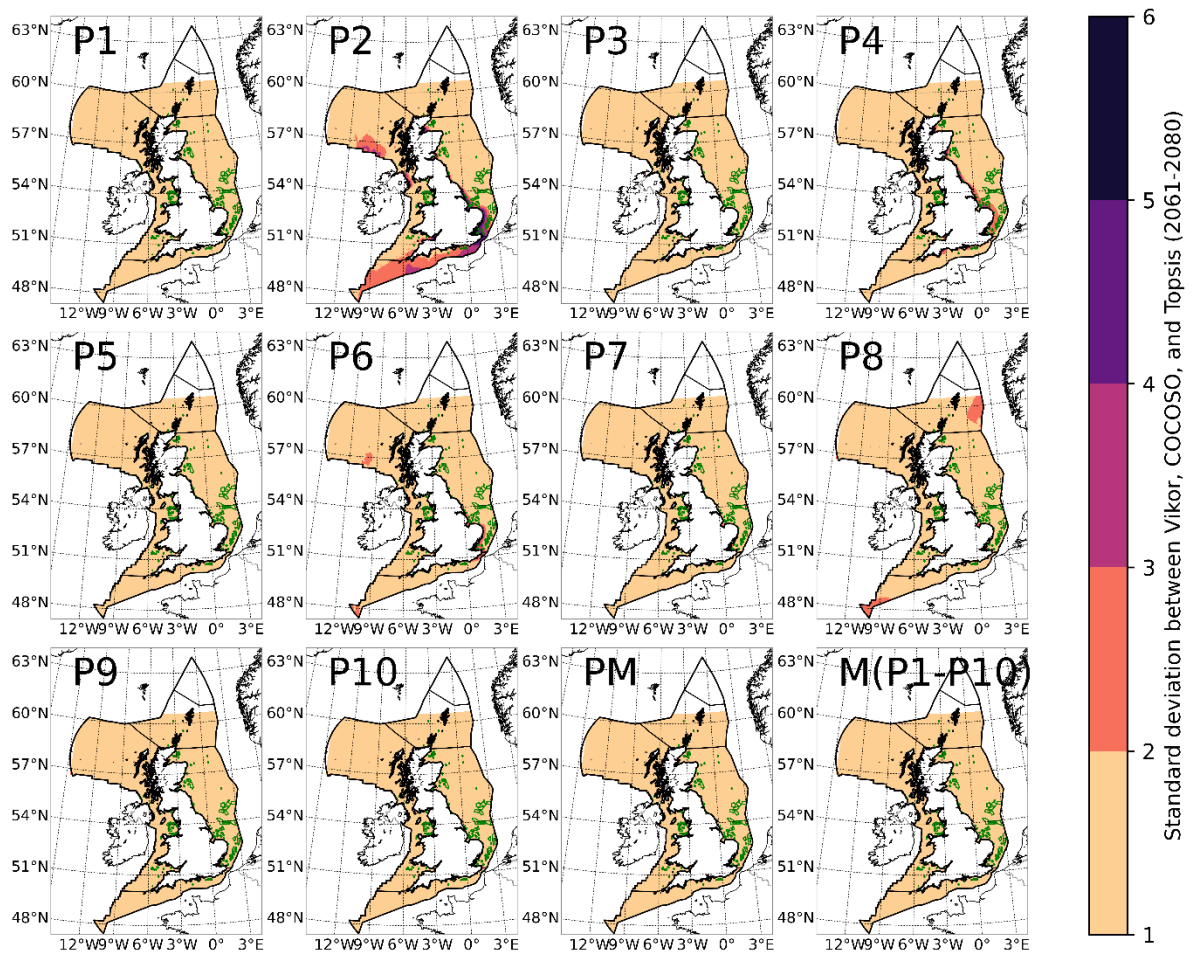


Figure 7.12. The standard deviation between vikor , COCOSO, and topsis for each of the 10 participants in the 2061-2080 scenario. P1 to P10 represent the standard deviation corresponding to the weighting of each of the 10 participants. PM is the standard deviation using the mean of the normalised weights for Participants P1 to P10. M(P1-P10) is the mean of the final ranking in plots P1 to P10

7.8 Stage 4 (Part 2) - Correlation tests

Correlation analysis is a bivariate statistical method employed to quantify the degree of association between two variables and determine the nature or direction of this relationship [166]. We have tested the correlation between Vikor, Cocoso, and Topsis for the map that represents the mean ranking of the ten participants; see Figure 7.6, Figure 7.7, and Figure 7.8 plot M(P1-P10) using two different correlation tests, Pearson correlation (parametric test) [152] and Kendall Tau rank correlation (non-parametric test) [153].

7.8.1 Pearson Rank Correlation Coefficient

The use of correlation coefficients allows for the comparison of obtained results to determine their degree of similarity. This research uses the Pearson rank correlation coefficient to compare ranking lists obtained through various MCDA methods. The Pearson correlation coefficient is a widely used statistical measure that quantifies the strength of the linear association between two variables. It provides insight into the degree of the linear relationship between these variables and ranges from -1, denoting a perfect negative correlation, to 1, indicating a perfect positive correlation. Furthermore, a Pearson correlation coefficient value of 0 signifies the absence of a linear correlation between the two variables [152].

$$\rho(x, y) = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}} \quad (7.18)$$

x_i and y_i are the variables to be tested, $\rho(x, y)$ is the Pearson correlation coefficient between x and y variables, $\bar{x}$ and $\bar{y}$ are the mean of variables x_i and y_i , respectively.

The Pearson correlation between Vikor, Cocoso, and Topsis methods using the mean of the ten participants ranking map in the baseline period gives a high positive correlation between the three MCDA methods equivalent to 0.99.

7.8.2 Kendall Tau Rank Correlation Coefficient

Kendall's Tau represents a non-parametric metric for assessing associations among columns of ranked data [153]. Kendall's measure the monotonic relationship between two variables. The Tau correlation coefficient, derived from this analysis, yields a numerical score within the range of 0 to 1, where a value of 0 signifies the absence of any discernible relationship, and a value of 1 indicates a complete and perfect relationship.

Figure 7.13 shows Kendall's Tau correlation between Vikor, Cocoso, and Topsis methods using the mean of the ten participants ranking map in the baseline period. The high value correlation between the MCDA methods ranged between 0.93 to 0.94.



Figure 7.13. Kendall correlation between Vikor, Topsis, and Cocoso for the mean of the 10 participants ranking.

The two correlation tests that we have considered, Pearson correlation [152] and Kendall Tau rank correlation [153], have agreed on the strong correlation between Vikor, Cocoso, and Topsis MCDA methods using the mean of the ten participants ranking in the baseline scenario. The following stage will compare the baseline scenario to the two future periods (2021-2040 and 2061-2080) to understand the change in preferred locations of siting future OWFs.

It is essential to understand not just the future change compared to the baseline period (which represents how the existing OWF will be affected by climate change in the future). Still,

the overall comparison between the four regions is essential. This comparison will allow a more comprehensive framework for future policies and OWF installation. Because one region can experience a decrease in the preference locations in the future compared to the baseline period, simultaneously, the overall ranking category for the baseline and two future periods can be higher compared to another region.

Figure 7.14 shows a statistical comparison between the East, South, West, and North regions for (a) Vikor, (b) Cocos, and (c) Topsis, taking into consideration that the regions are defined by aggregation of all (or part) of 23 of the shipping forecast areas. It can be seen that using the three MCDA methods, the West region has more advantageous locations for siting OWFs, with ranking 2 for the first quantile of the cell grids. On the other hand, the area in the south of the region exhibits higher ranking categories compared to the northern areas for the baseline period and in the first future period there is an increase in ranking around latitude 54° N (intersecting with Irish sea area) and expands toward Malin area in the second future period, see Figure 7.15 for the spatial description for baseline and two future periods. For example, Fastnet, Lundy, and the south of Irish sea. Also, the West and North regions have the lowest 75 percentile of the cell grid, equal to category 8 of the ranking for the majority of cell grids. It is worth considering that for the baseline period, the eastern area of the North region (Viking shipping region) ranks higher than the western area (Fair Isle), but that corresponds to a decrease in ranking in the second future period. The South region has fewer advantageous OWF siting locations in 2021-2040, equivalent to ~7 to 10; this range is decreasing notably in 2061-2080 for a degree equivalent to ranking category ~3 to 7 in Vikor and Cocos methods, indicating more advantageous locations. The East region shows a high ranking range from 6 to 9 in the baseline period, reflected in high ranking in all areas in the region, but more around the coastline, specifically in the Tyne area and a smaller ranking toward the open sea area. For

the second future period in the East region, the ranking range is increasing ~ 8 to 11, but this increase is more in open sea area compared to Tyne area.

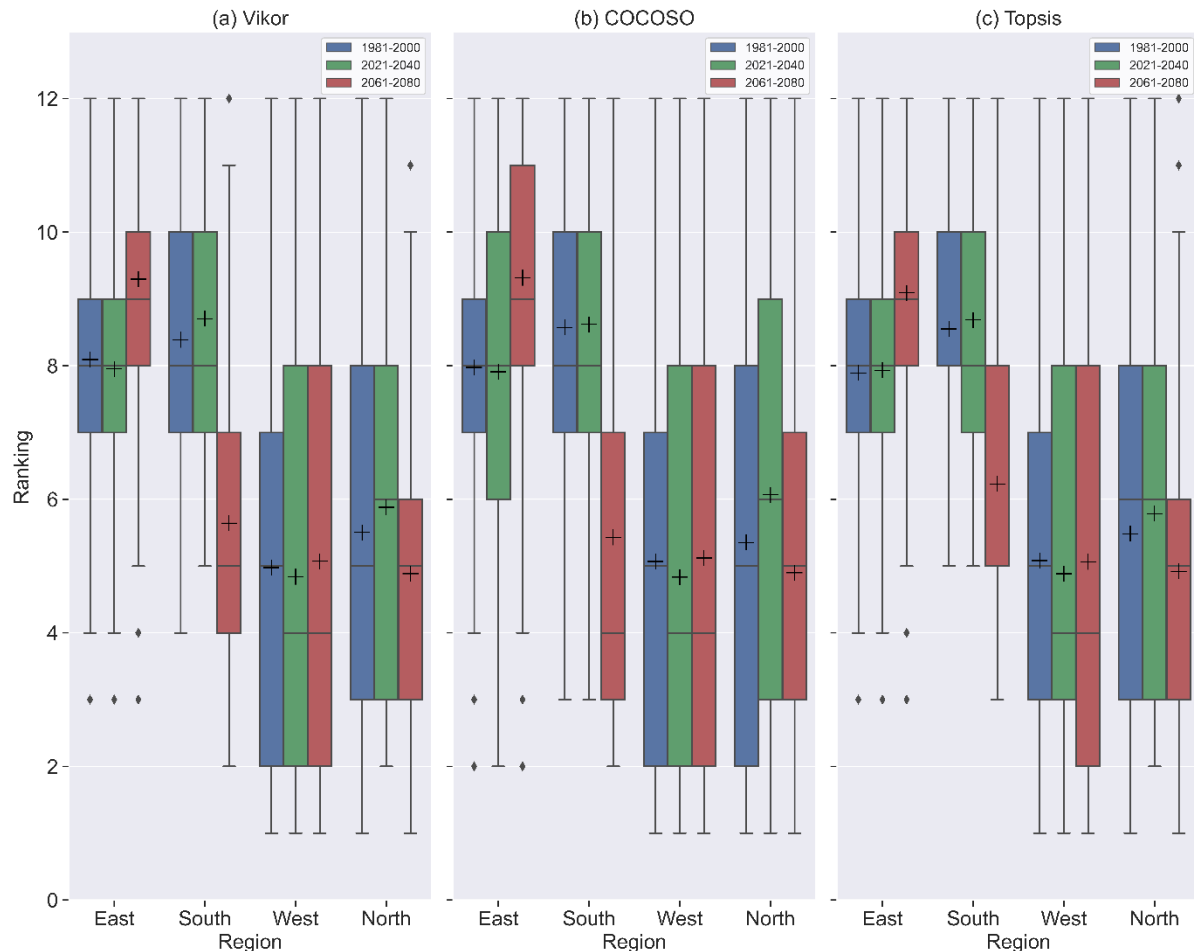


Figure 7.14. Box plots show the 12 ranking categories for three periods (1981-2000 (blue), 2021-2040 (green), 2061-2080 (red)) among three MCDA methods, (a) Vikor, (b) Cocoso, and (c) Topsis. Each plot's four comparison panels for the four regions, East, South, West, and North. The box holds the interquartile ranges (IQR), the midline represents the median, and the plus marker represents the region mean. The thin vertical black line represents the rest of the distribution, except for points determined to be “outliers”. The whiskers show the maximum and minimum values. The points beyond the thin vertical lines are outliers.

7.9 Stage 5 (Results) - MCDA using baseline and two future periods.

This section compares the ranking of the three MCDA methods in baseline and two future periods. The mean of 10 participants ranking is used in the baseline, and two future periods will be used for each of the three MCDA methods, Vikor, Cocoso, and Topsis. Figure 7.15

shows the first left column's baseline periods (1981-2000). As discussed before, the trend of having more preferred locations (ranking category from 1 to 6) exists in the northwest across the three MCDA methods. The middle and right columns show the difference between 2021-2040, 1981-2000, and 2061-2080, 1981-2000 across three MCDA methods, respectively. The positive change indicates a fewer advantageous location (ranking has increased in the future, which means fewer advantageous locations), and the negative range of values means more advantageous areas (ranking has decreased in the future, which means more advantageous locations).

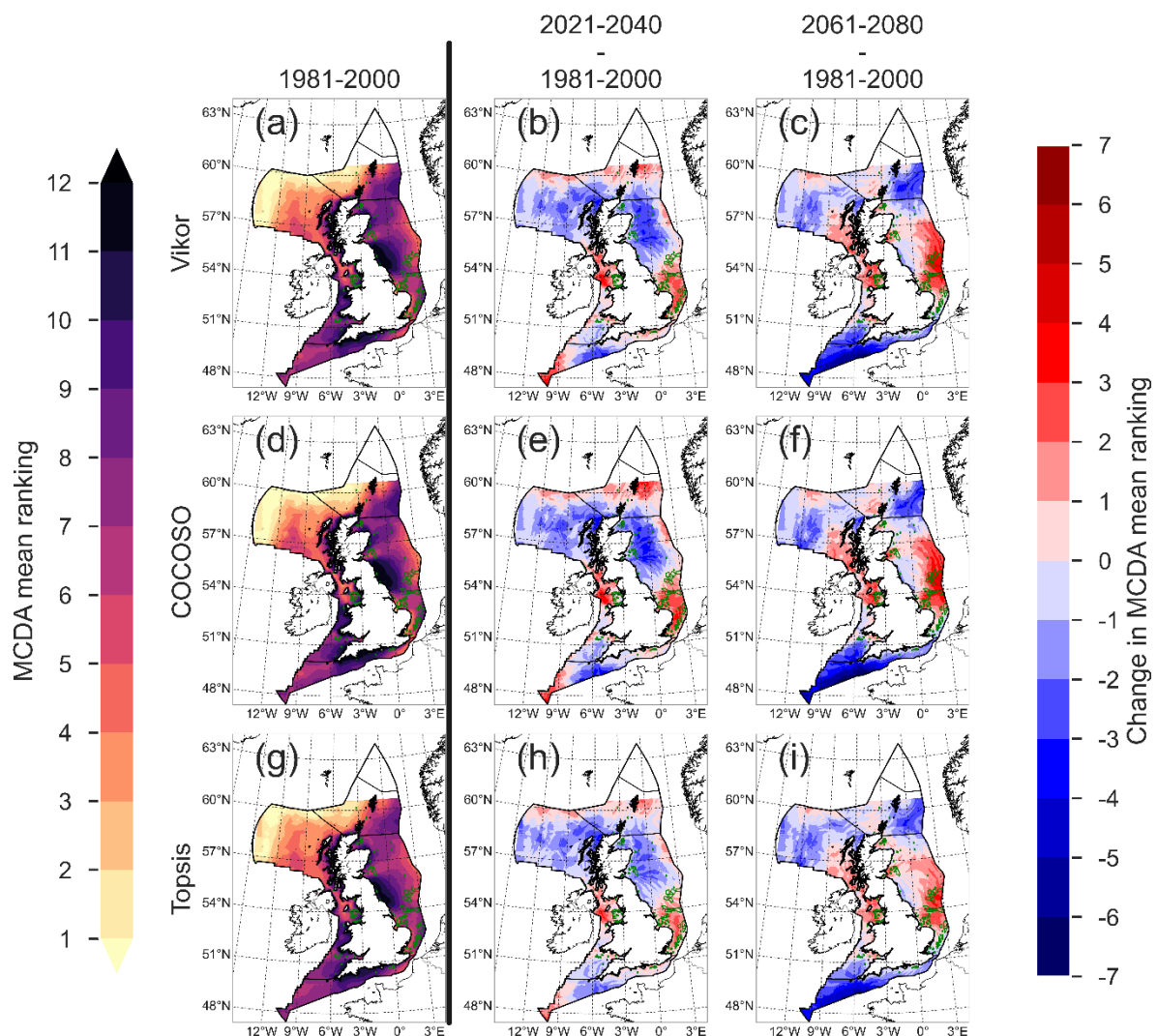


Figure 7.15. Spatial map representing the 12 ranking category for the mean ranking of the MCDA methods, rows from 1 to 3 represent the three MCDA, Vikor, Cocoso, and Topsis, respectively, and column (a) shows the climate period 1981-2000, column (b) 2021-2040 - 1981-2000, and column (c) 2061-2080 - 1981-2000. Black

outer boundaries represent the EEZ, and black internal boundaries represent four regions considered in the study. The green lines represent the fixed bottom wind farms and floating wind farms in UK offshore area. The data include all pre-planning, planning, construction, and operational phases.

Figure 7.16 (a) and (b) in row 1 conclude the results in Figure 7.15 by having specific values for all cell grid that shows an agreement of positive, negative, or no change across the three MCDA methods using the maps representing the mean of ranking categories. Doing so will give us more confidence in locations that agree with the three MCDA methods. The value of 1 indicates areas that agree on positive change between the three MCDA methods (fewer advantageous areas). The value of -1 indicates areas that agree on negative change between the three MCDA methods (more advantageous areas). Moreover, zero values refer to areas where the three MCDA methods agree on no change in the future compared to the baseline period for the three MCDA methods (neutral preference areas). Figure 7.16 (a) shows the agreement for changes in 2021-2040, and Figure 7.16 (b) shows the agreement for changes in 2061-2080 across three MCDA methods.

It can be seen from Figure 7.16 (a) and (b) that there is an agreement to decrease the preferences in locations of the bulk of the currently installed OWFs in the East region. Also, there is a decrease in preference for areas in the West region that span some of the existing installed OWFs. These reduced preference locations in the East and the West regions are the results of the consistent decrease in most of the criteria chosen in this study in future periods. For example, WPD shows up to ~14% decrease in all locations except east of the Viking area in the North region and South of Malin, Irish Sea, Lundy, and Fastnet in the West region and the South region except Fitzroy area in the near future. For the far future, the decrease is everywhere except in the east of the Forties and Dogger, in a location that intersects between these two areas. COV has a ~15% increase everywhere, except for locations west of Tyne in the East region for the near future. MV and SV have up to ~30% increase in the East region and the West region in 2061-2080 and ~17% in 2021-2040 in the North region in MV and the

South region in SV. The 35 m/s and 50-year factors have a ~33% decrease in the far future in the East region (in Dogger and Humber) and in the West region (in Irish Sea, Lundy, and Fastnet). At the same time, low wind criteria have a ~80% decrease in the East region between latitude 51° N and 57° N in the near future in Humber, Thames, and east of Dogger and the same increasing percentage in 2061-2080 in the West region. The CF has up to ~20% decrease in 2041-2080 for all locations.

Figure 7.16 (a) shows more advantageous locations in siting OWF in the northwest of the UK EEZ for 2021-2040. It is worth noting that locations in the northwest near the coastline have a low agreement with ERA5 data (OP <90%), as seen in Figure 3.1. Moreover, in the 2021-2040 period, areas near the northeast of the UK EEZ may be attractive for OWF installations, as they have locations with decreased ranking or no change in ranking category compared to the baseline scenario. Figure 7.16 (b) shows a preference for OWF installation northwest of the EEZ for the 2061-2080, but it spans a small area compared to the 2021-2040 period in Figure 7.16 (a). Moreover, for 2061-2080, there is more advantageous area in siting OWF in the South region of the UK EEZ. Figure 7.16 (c) and (d) shows the overlap between three MCDAs using the mean of the normalised weighting map in 2021-2040 and 2061-2080, respectively.

A similar trend to what was noted in Figure 7.16 (a) and (b) stresses the importance of reconsidering planning for future OWF sitting. Also, Figure 7.17 and Figure 7.18 show the overlap between the three MCDAs for Participants 1 to 5 and 6 to 10, respectively. In general, there is a pattern in the trends of increasing ranking category in East region locations and decreasing ranking category in the Northwest of the UK EEZ. There is some uncertainty in the strength of this pattern with the weightings from participants 1, 3, 4, 5, 6, 7, 8, and 9 resulting in a strong pattern and the weighting of participants 2 and 10 resulting in a weak pattern (see Figure 7.17 and Figure 7.18).

We conclude from Figure 7.16, Figure 7.17, and Figure 7.18 that policies need to be revised regarding future OWF installation, and reconsideration is necessary if repowering the existing installed OWFs in the East and West regions is required. A hybrid installation for multiple renewable energy resources in these locations can be a reasonable precaution for future planning in installing OWFs to ensure meeting demand and achieving net zero. Moreover, a more distributed installation of OWFs away from the bulk of OWFs installation will greatly benefit from preventing capacity output variation and provide a more reliable capacity output in all seasons. The recommendations for siting OWFs should take into consideration the limitation of using one wind turbine model (17MW) across all EEZ locations and the uncertainty that arises from using one ensemble from UKCP18 as shown in Chapter 3. For the ensemble '01' used in the thesis, the locations in the northwest near the coastline (east of Hebrides and Malin areas) and locations in the south of Plymouth Sole have a low agreement with ERA5 data using the OP analysis (OP <90%). On the other hand, these locations have the lowest variation corresponding to ERA5 (less than 0.0003) and locations in the East region, close to the coastline (Cromarty, Forth, Tyne, and west of Humber have a higher variation up to 0.6).

It can be seen that the areas identified for fixed-bottom offshore wind farms (recommended by crown estate, see Figure 1.2) overlap the areas that have increased in ranking using the mean of the ranking map, see Figure 7.16 (a) and (b), except for limited locations in the northeast of the UK and in the south. On the other hand, areas identified for floating offshore wind farms overlap with the areas of decreasing or no change in ranking in locations in the northeast and the south of the UK in 2021-2040. Also, for 2061-2080, the South region is recommended for floating substructure installations. This concludes that future planning may rely more on floating offshore wind farm technology, and the development of this technology to a utility-scale may be needed.

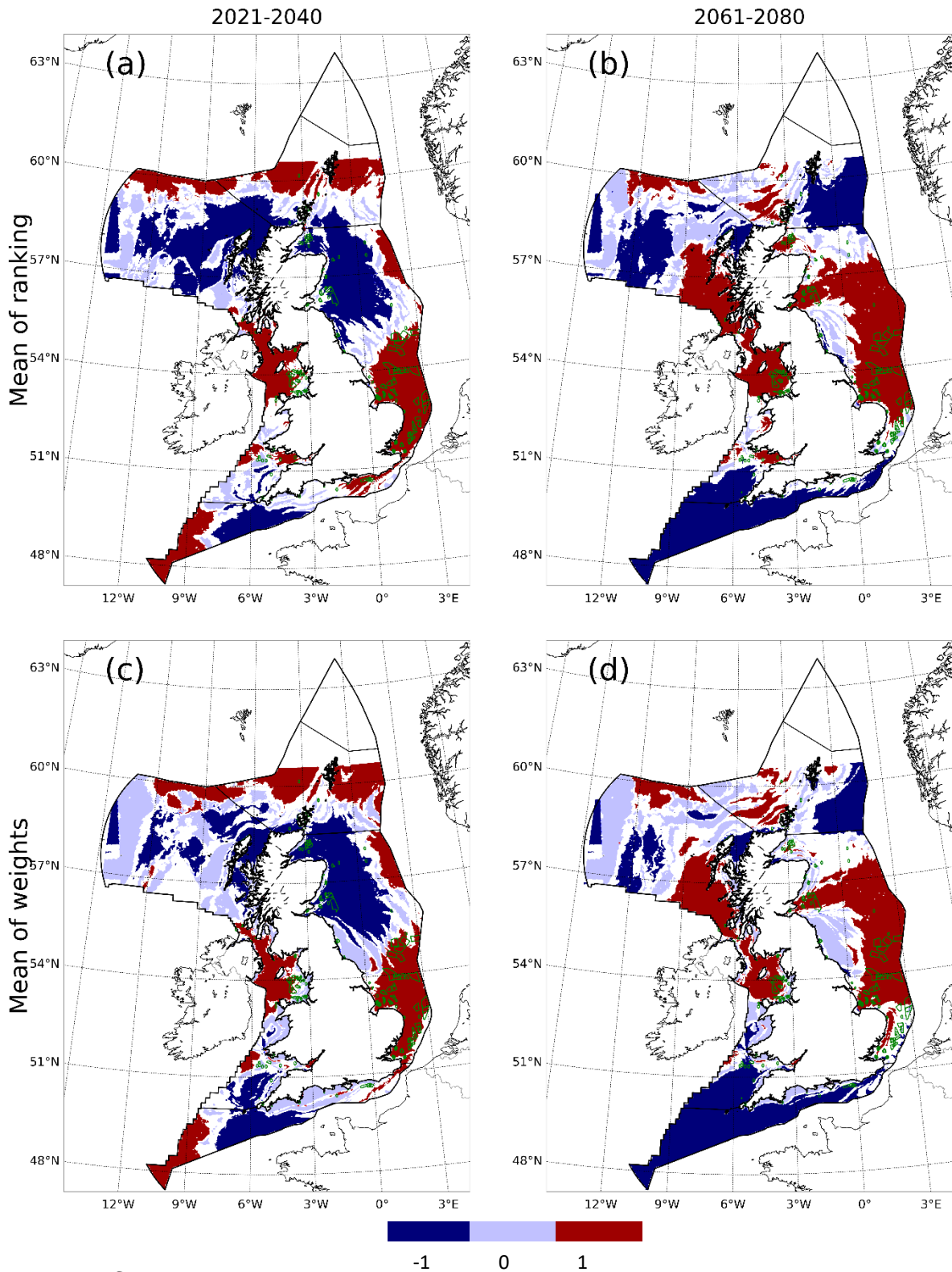


Figure 7.16. Overlap of positive, negative, and no change between the mean of the ranking category (row 1) and the mean of the weights (row 2) for Vikor, Cocoso, and Topsis in 2021-2040 (column 1) and 2061-2080 (column 2). Dark blue holds the value of -1, indicating ranking decrease = more advantageous locations; light blue has a value of 0, meaning no change and red colour holds the value of 1, indicating ranking increase = fewer advantageous locations. White colour locations inside the UK EEZ boundaries indicate no agreement between the three MCDAs.

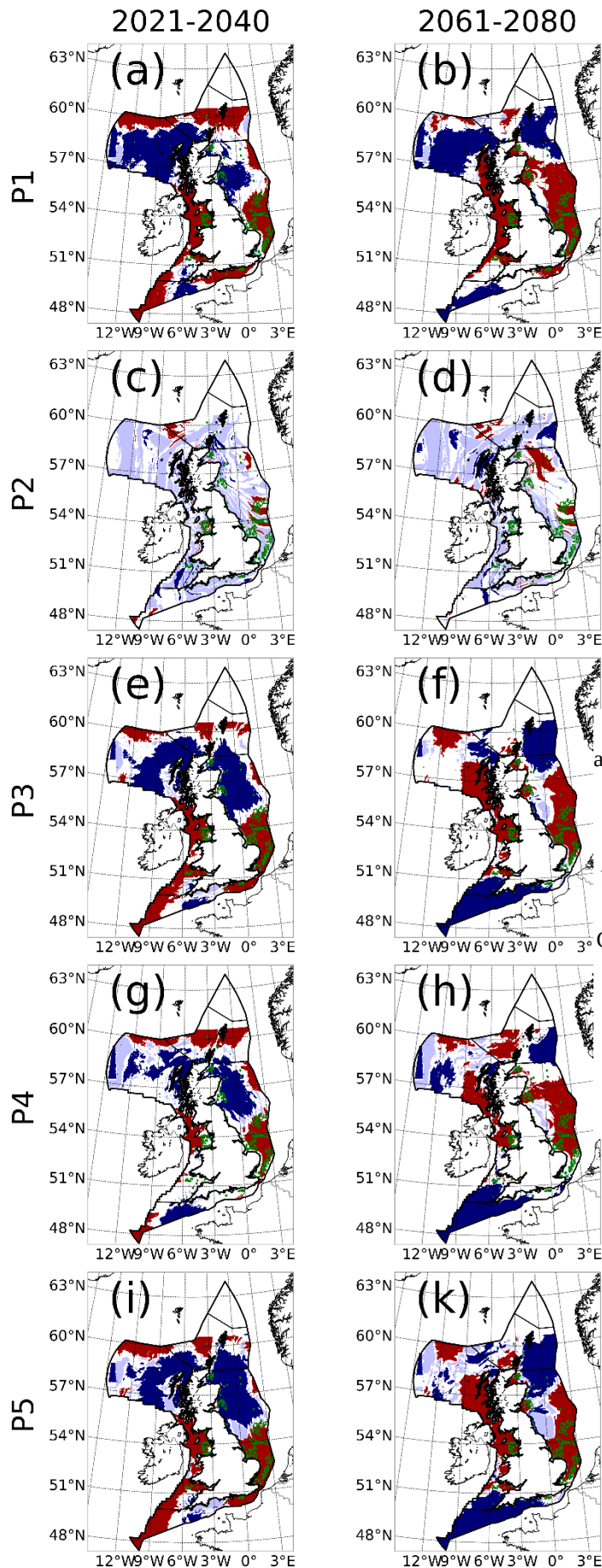


Figure 7.17. Overlap of positive, negative, and no change of Vikor, Cocoso, and Topsis for first five Participants (P1 to P5). Left column show the changes in 2021-2040 and the right column show the changes in 2061-2080. Dark blue holds the value of -1, indicating locations with a decrease in the ranking across Vikor, Cocoso, and Topsis; light blue has a value of 0, meaning no change and red colour holds the value of 1, indicating an increase in ranking. White colour locations inside the UK EEZ boundaries indicate no agreement (positive, negative, or no change) between the three MCDAs.

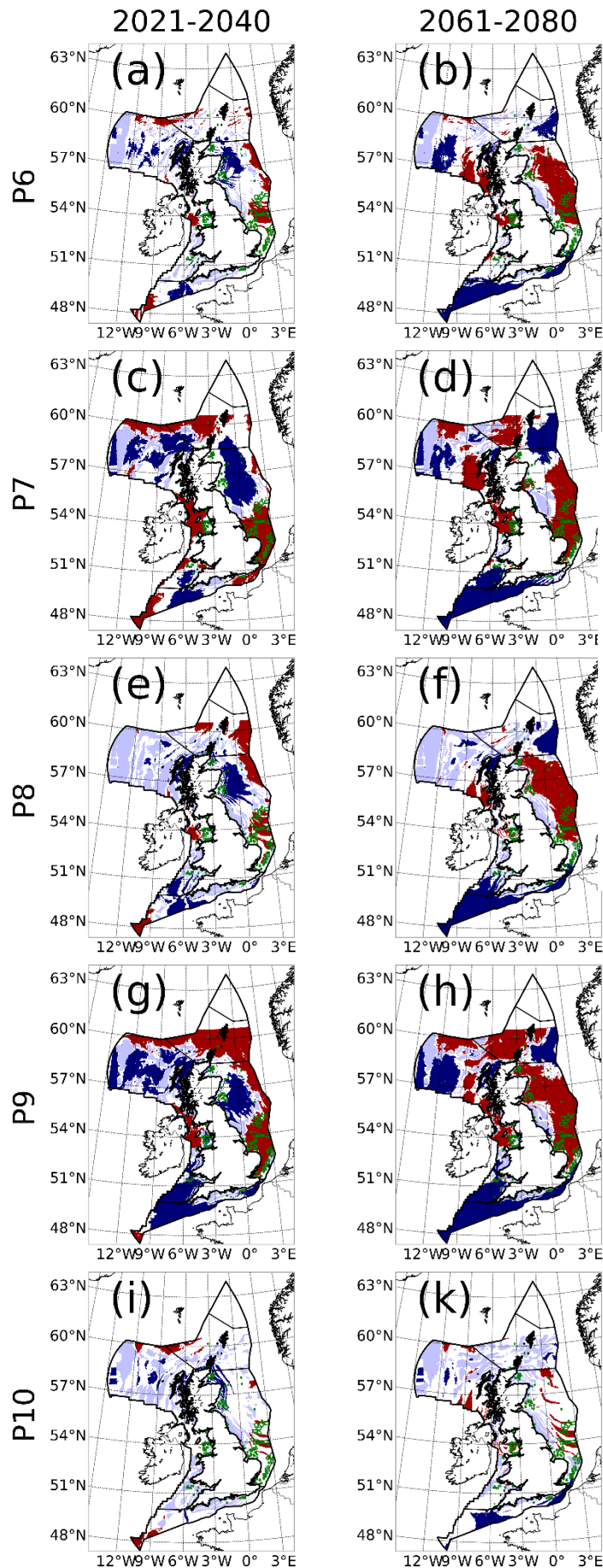


Figure 7.18. Overlap of positive, negative, and no change of Vikor, Cocoso, and Topsis for second five Participants (P6 to P10). Left column show the changes in 2021-2040 and the right column show the changes in 2061-2080. Dark blue holds the value of -1, indicating locations with a decrease in the ranking across Vikor, Cocoso, and Topsis; light blue has a value of 0, meaning no change and red colour holds the value of 1, indicating an increase in ranking. White colour locations inside the UK EEZ boundaries indicate no agreement (positive, negative, or no change) between the three MCDAs.

It is worth highlighting that there are locations that overlap both substructure technologies (fixed-bottom and floating) and simultaneously intersect our recommendation for future siting considering the ten factors. The recommendations for floating and fixed bottom substructure installation are only given for locations shown in Figure 1.2, which doesn't cover the EEZ in the north of the UK. The East, West, North, and South regions are defined by aggregating all (or part) of 23 of the shipping forecast areas.

Figure 7.19 (a) and (b) shows the intersection between the recommended locations in this research (see Figure 7.16 (a) and (b) for mean of ranking) and the recommended locations by the crown estate for fixed bottom substructure seen in Figure 1.2. Also Figure 7.19 (c) and (d) shows the intersection with the floating substructure recommended by the Crown Estate. In Figure 7.19 (a) and (c), we found an intersection between these three aspects in the northeast (highlighted in green circle for 2021-2040); this area currently (which intersects with Forth, Tyne, Forties, and Dogger) has installed wind farms, see Figure 3.8, which indicates a promising wind capacity generation in case of repowering in 2021-2040. Also, in Figure 7.19 (b) and (d) for the 2061-2080 period, we found these three aspects in locations in the south of the UK (highlighted in a green rectangle) covering all shipping areas in the region (Dover, Wight, Portland, Plymouth, Fitzroy, and Sole). In the first future period, Figure 7.19 (a) and (c) show that the West region does not show recommended locations for Irish sea area for both fixed bottom and floating technologies, which remain the same for the second future period. In the South region, Figure 7.19 (c) shows recommended areas in Plymouth and Sole for installing floating substructures that expand in the second future period in Figure 7.19 (d) to cover more areas in the South region, as mentioned before. There is a recommended locations in the northwest of the EEZ intersecting Hebrides, Malin, Bailey, and Rockall. Still, we don't have the recommendations from The Crown Estate for the substructure they recommended. These areas are in the open sea, where mainly floating substructures will be needed for high-depth

locations. On the other hand, these recommended areas are expanding less in the second future period.

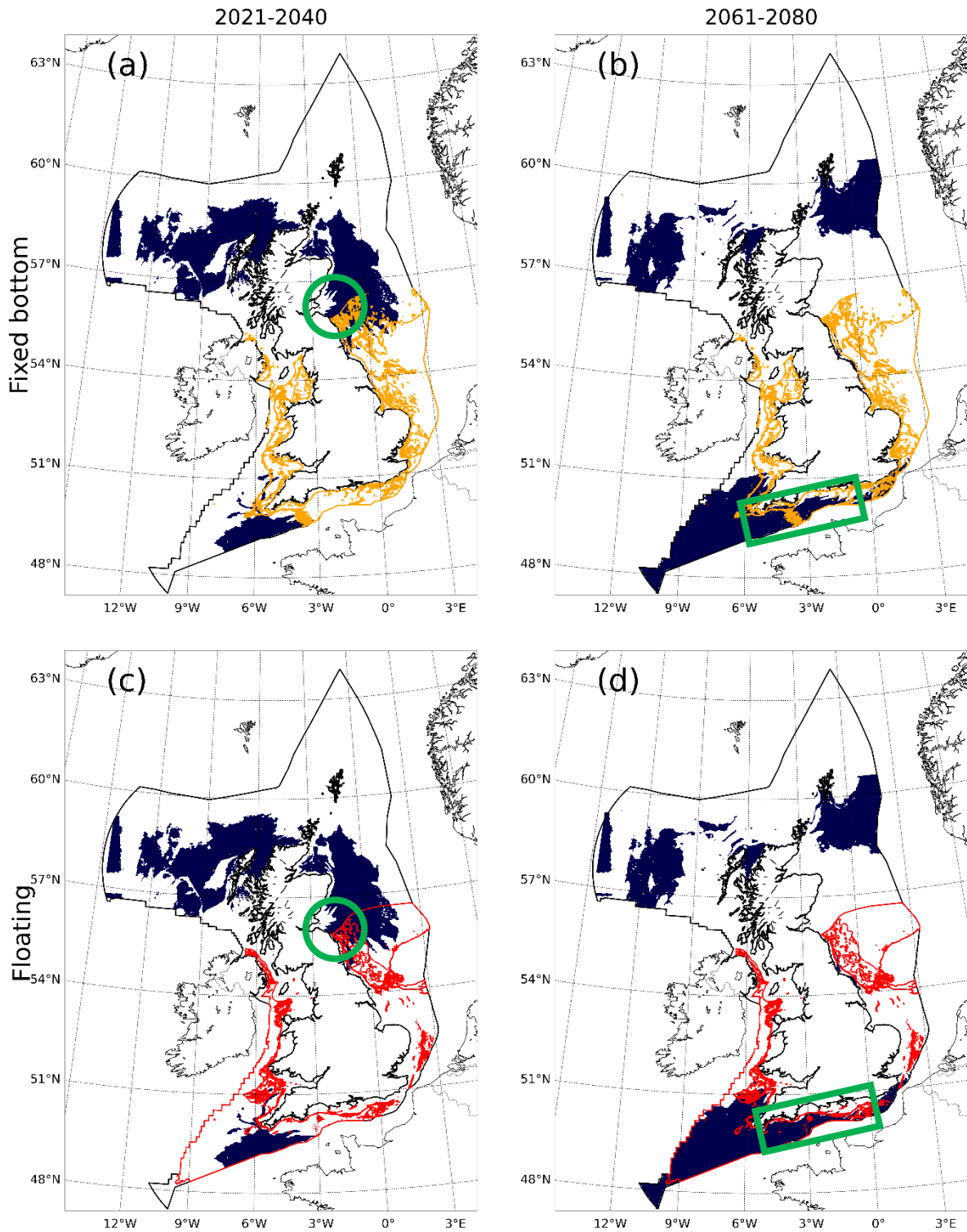


Figure 7.19. Overlap of recommended locations (negative change in ranking category) for the mean of the ranking category ranking across Vikor, Cocomo, and Topsis in dark blue. In plots (a) and (b) boundaries of the crown estate fixed-bottom substructure resources is in yellow lines and in plots (c) and (d) boundaries of the crown estate floating substructure resources is in red lines. Column 1 represent 2021-2040 and column 2 is the 2061-2080 period. The green highlighted areas indicate locations identified by the crown estate suitable for fixed-bottom and floating installation simultaneously overlap our recommendation for future installations.

From Figure 7.14 (a), (b), and (c), the East region generally has a less advantageous locations in the three time periods. At the same time, Figure 7.19 shows specific locations in the East region that intersect in the current bulk of OWF installation are also not recommended for future installation as there is a noticeable increase in ranking in future periods compared to the baseline period.

The North and the Northwest of the UK EEZ have the lowest ranking category compared to all other locations for the three time periods. At the same time, the Northwest region has a considerable number of areas with a decrease in the ranking category in the two future periods. In contrast, current OWF installations prioritise the East region over the northwest, driven by varying seabed conditions. The East offers a substantial potential for cost-effective fixed-bottom technology, whereas the northwest predominantly necessitates pricier floating technology solutions.

Chapter 8 Conclusions and future work

This chapter summarises and discusses the key findings of this thesis as well as suggesting numerous avenues for further research at the interface between future planning, financial aspects and geophysical constraints.

8.1 Conclusions

The UK offshore area has been divided into four regions: East, South, West, and North. Taking into consideration that the regions are defined by aggregation of all (or part) of 23 of the shipping forecast areas. The thesis analysis was done by comparing the four regions. A novel approach is proposed to identify suitable EEZ regions to site future OWF in the UK. The work investigates the future change in mean wind speed and maximum wind gust in the UK EEZ using a cutting-edge 2.2 km horizontal resolution UKCP18 dataset. The maximum wind gust data from UKCP18 and ERA5 are based on different time durations (10-minute vs. 3-second gusts). Neither dataset perfectly matches the 10-minute sustained gust definition from UKCP18. The UKCP18 CPM for wind gusts has been used in multiple studies in the UK and Europe [132], [133], [134]. It shows a good representation of wind gusts by comparing them to ERA-Interim and observational datasets. This research uses mean wind speed datasets for validation. The study selects the 01 ensemble of mean wind speed data for further analysis, as both the mean wind speed and maximum wind gust are derived from the same climate model. This ensures consistency in the predictive model for future siting. On the other hand, the spatial variation analysis across the UK EEZ reveals that ensembles 01 to 15 generally exhibit a low variation range, between 0.003 and 0.6, while the ensemble mean and median show a higher variation, reaching up to 2.12. Among the ensembles, 07, 08, 12, 13, and 15 stand out with the highest average variation across all EEZ locations (~ 0.3), whereas ensemble 04 demonstrates

the lowest variation (~ 0.2). This suggests that while most ensembles maintain relatively consistent variation, certain ones display notable deviations.

The recommendations provided for the EEZ locations in the UK are subject to several important limitations. First, the use of a single wind turbine model (a 17 MW turbine) across all EEZ locations introduces a degree of generalization that may not fully capture site-specific characteristics. Different locations may have unique wind profiles, which could require different turbine specifications for optimal performance. By relying on a single turbine model, the recommendations might not account for these variations, potentially affecting the accuracy of energy yield predictions and system design recommendations.

Furthermore, the UKCP18 ensemble data used in the analysis introduces additional uncertainty, particularly regarding ensemble variation and agreement with ERA5. The ensemble '01' used in the thesis exhibits variation in certain locations, particularly in the northwest near the coastline (east of Hebrides and Malin areas) and in the south near Plymouth Sole. These areas demonstrate a low level of agreement with ERA5 data, as reflected in the OP analysis. This low agreement introduces uncertainty in the reliability of the projections for these regions. However, it is notable that these same locations show the lowest variation when compared to ERA5, with a variation of less than 0.0003.

In contrast, other areas, particularly in the East region close to the coastline (Cromarty, Forth, Tyne, and west of Humber), exhibit much higher variability, with differences reaching up to 0.6. These variations further complicate the interpretation of the data, as different ensemble members produce inconsistent projections for different regions. The discrepancies between ensemble '01' and ERA5 underscore the need for careful consideration of the uncertainties involved when making long-term projections and recommendations. Therefore, while the recommendations offer valuable insights, they must be interpreted with caution,

particularly in regions where the data uncertainty and variation are more pronounced. Future studies should consider incorporating a wider range of turbine models and applying the model on different ensembles to provide detailed comparisons and reduce uncertainty in results.

Our analysis considered multiple factors, including WPD, seasonal and monthly stability, CF, extreme LWE and HWE, WD, and DC. The 17 MW turbine was selected to align with industry trends toward larger turbines in offshore wind farms. These turbines offer higher capacity factors and better performance in regions with stronger winds, like the North Sea. The thesis focuses on the 17 MW turbine as representative of future offshore wind energy development, demonstrating that larger turbines outperform smaller models, such as the V117-3.3 MW, in terms of capacity factor. While smaller turbines were included for comparison in Chapter 4, the results highlight the increasing relevance of larger turbines in capturing wind energy more efficiently for future installations.

To conclude the results of the work conducted, the thesis's main finding will be briefly summarised below:

Wind production: We provided recommendations for the future installation of OWFs by revealing the locations within the UK EEZ with the least risk of decreasing the long-term WPD and its stability. The daily pressure and temperature data have been used in the WPD calculation for the three climate periods, leading to precise estimation for future changes in WPD. Five factors have been used to assess future recommendations: WPD, MV, SV, COV, and CF. The future siting recommendations are built on the future projection climate model. The wind data used are hourly and daily time steps, providing high accuracy in the results. Two methodologies are used to comprehensively estimate possible changes in wind energy. The first method is the RC calculation, which was used to gain insight into possible changes in the two future periods (2021-2040 and 2061-2080) compared to the baseline period 1981-2000.

The second method uses MAT corresponding to each of the five factors considered in the chapter. MAT is a reference point for identifying suitable EEZ regions for OWF installation.

Moreover, the seasonal investigation of the three climate periods for most factors has provided a detailed assessment of the siting recommendations. As a result, the assessment of seasonal WPD indicated a marked decrease of two classes during summer in both future periods. Furthermore, in the 2061-2080 period, the autumn season showed a similar decrease of two classes in locations below latitude 55° N. The 20 years projections indicate that the CF will consistently decrease in all regions in the two future periods, implying a higher risk of reduced energy production for the current installed OWF. Moreover, In the two future periods, the CF median is lower than the baseline in 50% of the years.

In general, according to the difference between the region's median and the MAT in future periods, the East region has not been included in any recommendation for future OWF expansion, using MV, SV, and CF, except for the winter season in COV analysis. Moreover, eastern region shows up to 20% increase in future periods for WPD in winter and spring corresponding to up to 40% decrease in summer and autumn. The North, South and West regions are the most resilient to future climate change according to most of the factors considered in the chapter.

Extreme LWE: The analysis provides recommendations for the future installation of OWF by revealing the locations within the UK EEZ with the least risk of increasing extreme LWE. The analysis uses different cut-in thresholds of 3 m/s, 4 m/s, 5 m/s, and 6 m/s to overview multiple cut-in wind speeds. Various aspects have been used to investigate future LWEs, such as the seasonal changes for the future duration of LWEs under cut-in wind speed thresholds. It is found that the summer season has shown the most significant durations of LWE among the

four seasons. Moreover, we investigated the future increase of low wind intensity by calculating the return period of 4 m/s, 5 m/s, and 6 m/s in 5 days running mean wind speed. As a result, the analysis showed more frequent LWEs near the coastline. Based on the calculations of the regional median for the return period and the Risk Ratio, it is proposed that the South region demonstrates a reduced likelihood of encountering more frequent wind speeds exceeding the specified cut-in threshold. This observation holds true specifically when considering cut-in thresholds of 5 m/s and 6 m/s during the time spanning from 2021 to 2040, compared to the historical period. We extended our research on the 4 m/s to investigate more intense durations: 6, 7, and 8 day running's mean wind speed. As a result, the West region is also recommended for OWF installation within the 2021-2040 period.

In general, the return period calculations for the 4 m/s threshold for the historical and two future periods resulted in emphasising the importance of considering future planning of wind turbines with cut-in wind speeds < 4 m/s in locations near the coastline.

Extreme HWE: To measure the potential risk of high wind speed increase, we used the wind turbine manufacturer's threshold for extreme loading U_{50} and the threshold for stopping operational states (35 m/s cut-out wind gusts). Our analysis indicates that the Beta distribution is the best to represents hourly wind gust data in the UK's EEZ. Using return period calculations, we determined the corresponding return period for the 35 m/s threshold and the wind gust threshold aligning with U_{50} . We examined the RC and RR for the four regions using three distinct time points for both U_{50} and 35 m/s. The RC was calculated using U_{50} allowed for identifying sites that are expected to experience varying degrees of impact from climate change regarding the installation of future OWFs. In particular, the East and North regions were found to have a more advantageous on OWF repowering during the 2021-2040 and 2061-2080 time periods, respectively (The recommendation for repowering is based on the direction

of change (whether an increase or decrease) between the baseline and future scenarios. The decision is made without considering the specific magnitude of the change but rather based on whether particular factors are expected to improve or decline). Conversely, the South region was less advantageous in both periods. Moreover, we assessed the RC associated with a 35 m/s return period and the risk of exceeding 35 m/s (no-operational threshold) over four regions for two future time windows. The results revealed that the North region offered the most advantageous conditions for existing wind farms, as the two future periods indicate a lower frequency of 35 m/s winds compared to the baseline period. Conversely, the South region was the least advantageous in both periods.

In general, the analysis of the three primary wind turbine operations and the no-operation status has led us to the conclusion that there is a requirement for a model that integrates the results of chapters 4 to 6 into a single preference map. Given the negative impacts of climate change, this model should consider the importance of multiple factors and aim to identify the most resilient future locations. We used various MCDA techniques to merge the ten leading factors impacting OWF siting. By doing so, we aimed to identify the most suitable sites for future OWF siting with the highest confidence among three different MCDA methods.

Based on the comparison of the change between the future and the baseline periods, it is less recommended to repower the current bulk of OWF in the East region, and this is not just because a large future increase in ranking is found in the location of the bulk installation area but also because it has the highest range of ranking category in the three climate periods. This is also applied to locations in the West region. The East and the West locations overlap with the Crown Estate recommendation of fixed-bottom offshore wind farm installation, which leads us to conclude that in case of replanning the future installation of OWF, the floating substructure will be heavily needed to be used in utility-scale to lower the cost. On the other

hand, the Northwest area has a greater preference for future OWF installation considering both future decreasing ranking and the range of ranking category.

In conclusion, the thesis investigated eight factors to identify changes in the two future periods and locate the region with the greatest resilience to climate change's negative impact. For the near future, WPD is more advantageous in the South region and the southern part of the West region, specifically the Irish Sea, Fastnet, and Lundy. CF has limited locations with a slight increase in CF ~2% in the west of the Irish Sea area in the West region. COV factor shows more resilient locations near the coast in Tyne area in the East region. MV has a more advantageous location in the South region and the Hebrides area in the West region. The SV has a more resilient location in the north of the West region, specifically Hebrides, Bailey, Rockall, and Malin. Also, in the North region in Fair Isle area and the north of the East region in Cromarty area. The return period corresponding to 35m/s factor has more advantageous locations in all areas above latitude 54° N. The 50-year return period factor shows more resilience locations in all locations above latitude 54° N, except the Irish Sea and the south of Malin area in the West region and the east of the Viking area in the North region. The return period corresponding to the 4m/s factor shows an advantageous location in the southwest of the UK, specifically intersecting the Lundy, Fastnet areas from the West region, and Sole area from the South region and the west of Forth area in the East region. According to most of the factors described, for the near future, the areas in the northwest of the UK EEZ are the more resistant to climate change, specifically, Hebrides, Bailey, Rokall, Malin and the west of the Fair Isle from the North region. Also, the South region is more advantageous for the WPD, MV, and Low wind factors.

For the far future, the WPD factor is more advantageous in the east of the intersection between Forties and Dogger, located in the East region. The COV is more advantageous in limited areas northwest of the EEZ intersecting Baily and Rockall areas in the West region.

The 35m/s and the 50-year return period factors show more resilient locations in the Fitzroy area in the South region and around latitude 57°N and above, intersecting Main, Rockall, Bailey, and Hebrides from the West region. And Fair, Isle, Faeroes, and Viking in the North region. In addition to Cromarty, Forth, and north of Forties. Finally, the South region has advantageous locations in the south of Plymouth, Sole, and Fitzroy. In summary, for the far future period, the north region and the northwest of the West region (Bailey, Hebrides, Rockall, north of Malin) are the more advantageous according to the majority of the factors.

For the three MCDA ranking results, the West region consistently shows more advantageous locations for (OWFs) across all MCDA methods, particularly in the first quantile. The South region exhibits a notable increase in favourable OWF siting locations, particularly around the Irish Sea and Malin areas, during the second future period. In the East region, higher rankings are observed near the coastline in areas like Tyne during the baseline period, with a shift towards more favourable locations in the open sea in the second future period.

From the comparison of the results of the MCDA model and the Crown Estate recommendations, in the South region, there are recommended areas for installing floating substructures, which will expand in the second future period. There are recommended locations in the northwest of the EEZ, covering areas like Hebrides, Malin, Bailey, and Rockall, suggesting the need for floating substructures due to high-depth locations, though specific substructure recommendations from The Crown Estate are unavailable.

In summary, this thesis provides valuable insights into the siting of OWFs in the UK EEZ. The research results pave the way for greater reliance on offshore wind production, thus contributing to achieving the net-zero targets. Our analysis can inform decision-making processes related to OWF siting and contribute to developing sustainable and efficient wind energy production systems.

8.2 Future directions

The use of RCP8.5 in this research provides a good understanding of the impact of future climate change on wind energy production in the UK offshore areas. Currently, RCP8.5 is the only available pathway in the 2.2 km UKCP18 UK grid, which is the necessary resolution to capture mesoscale events. In this research, we use the RCP8.5 scenario to ensure the most suitable siting for OWF in the future, even under the worst-case scenario. However, it is advisable to consider other pathways, such as RCP4.5, to have a broader and more diverse view of the expected changes and recommendations for future OWF installations.

The present research utilised the default ensemble (01) from the 2.2 km UKCP18 climate model. It is recommended that the analysis be reproduced using the remaining eleven ensembles and that sensitivity analysis techniques be used to determine the impact of the varying ensembles on the results. Such an approach would substantially reduce the uncertainty arising from climate models.

The analysis used hourly data over 20 years, covering a vast region like the UK EEZ at a 2.2 km horizontal resolution. Utilising the 6TB node within the University of Oxford Advanced Research Computing (ARC) High-performance computer cluster service was necessary to process the extensive data. Given the significant computational challenge, conducting the analysis utilising other ensembles was not feasible due to the long time required for processing. Furthermore, one ensemble and its associated outcomes necessitated 24 TB of memory from the ARC data storage systems.

It is important to note that using other wind turbine models with different capacities will affect wind energy production in UK offshore areas. It is recommended to consider multiple types of wind turbines with various rated capacities in the calculations and compare the results.

It will have a crucial impact on the results and the recommended regions for future OWF installations.

In addition to this study's outcomes, assessing the severity of storm surges and extreme wave height could provide valuable insights for future OWF siting. The UKCP18 dataset offers storm surge and extreme wave height projections at a 12 km horizontal resolution for the two future periods. Because of the extensive computation needed to process the data, this research did not include the storm surge and extreme wave height. Utilising diverse energy resource data, including wind and wave information, can enhance the overall decision-making process for the siting of hybrid renewable energy systems. Such an approach would lead to a more integrated and effective strategy for developing renewable energy resources.

Appendix A: 5th, 6th, 7th, and 10th percentile of daily mean wind speed

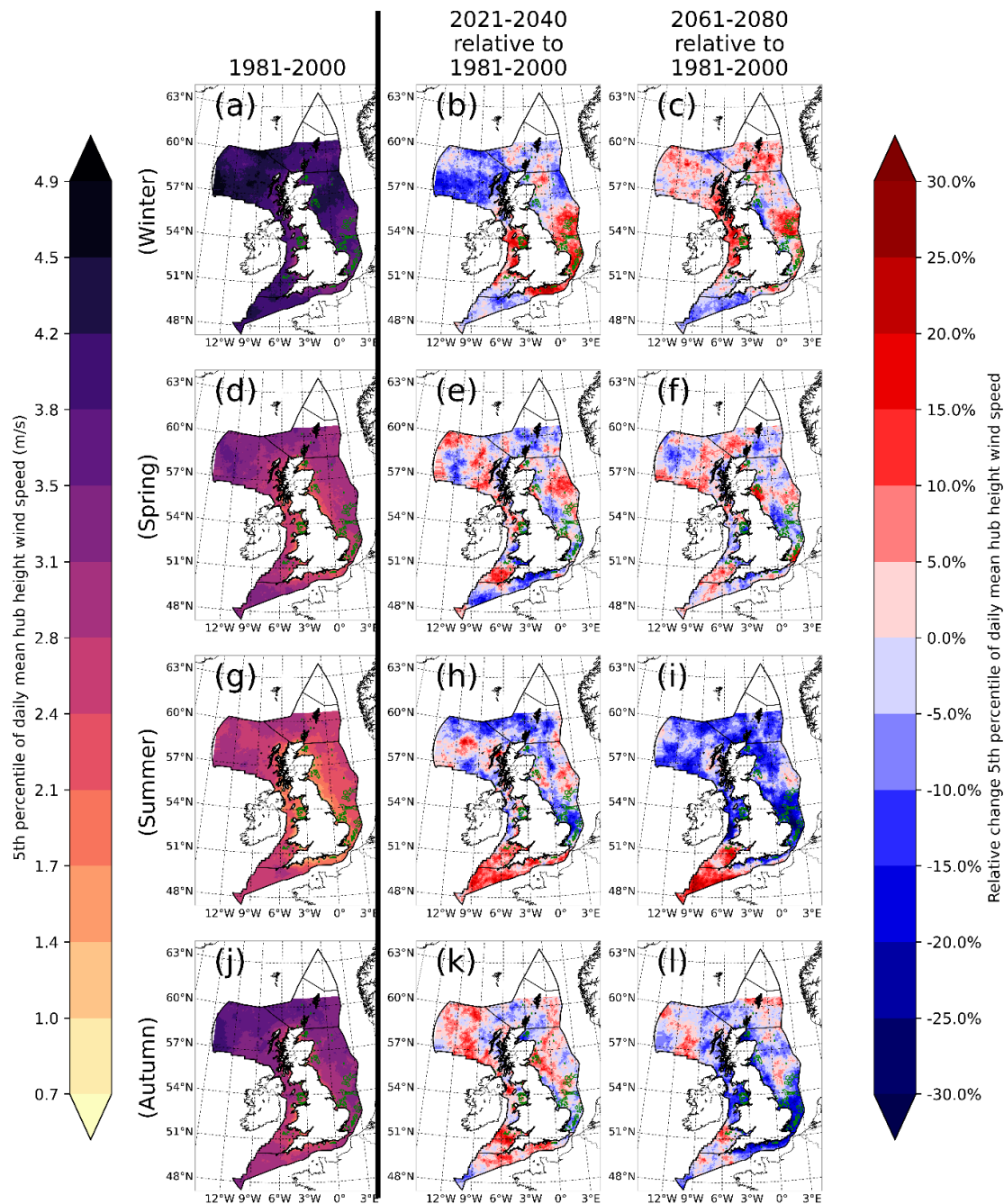


Figure A.1. Column one from left side: 5th percentile of daily mean hub height wind speed in the four seasons for the 1981-2000 scenario. Rows from 1 to 4 represent the four seasons: winter, spring, summer, and autumn. Column 2 and 3 from the left side shows the relative change of 2021-2040 and 2061-2080 to 1981-2000, respectively. The green lines represent the fixed bottom wind farms and floating wind farms in UK offshore area. The data include all pre-planning, planning, construction, and operational phases.

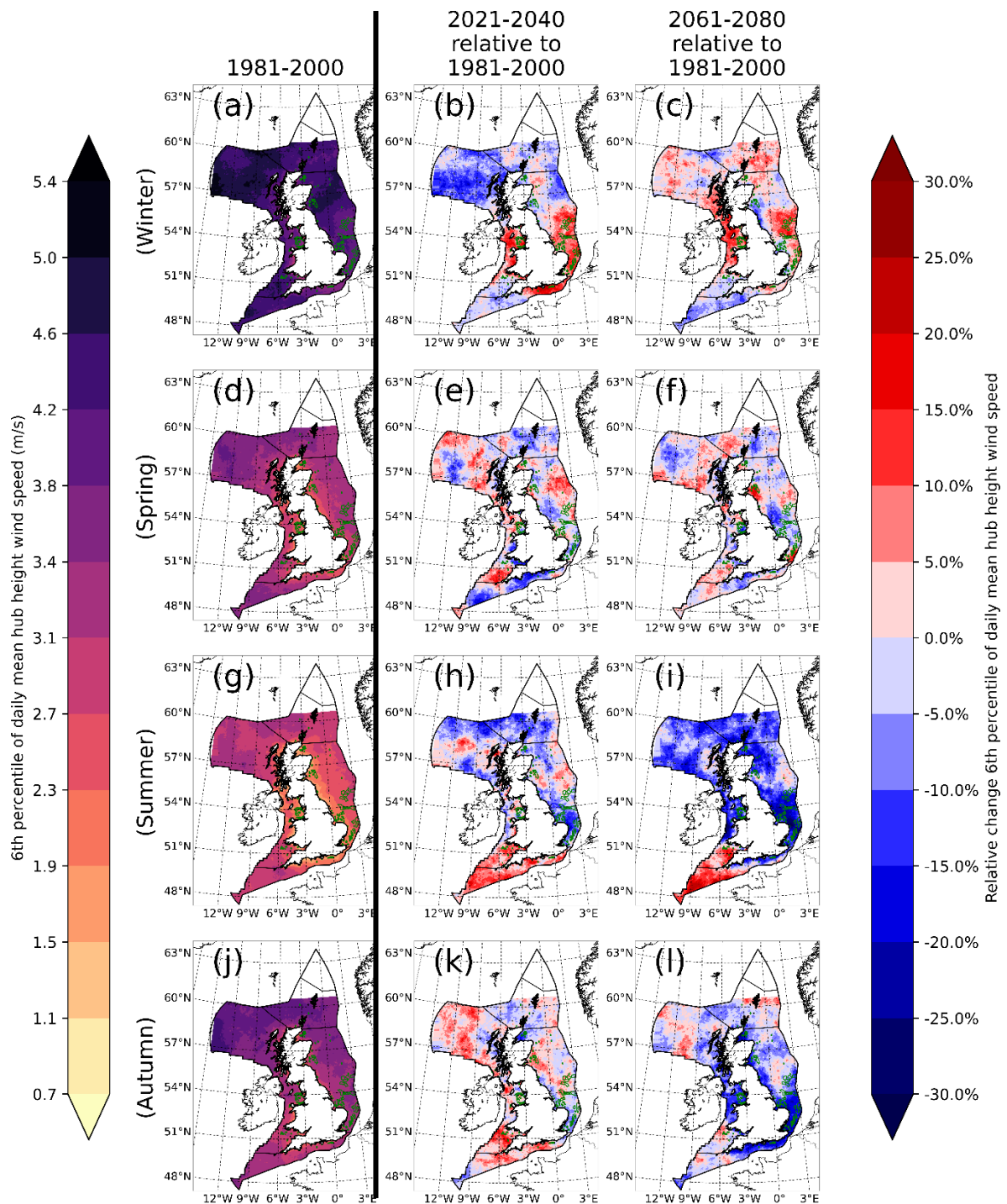


Figure A.2. Column one from left side: 6th percentile of daily mean hub height wind speed in the four seasons for the 1981-2000 scenario. Rows from 1 to 4 represent the seasons: winter, spring, summer, and autumn. Column 2 and 3 from the left side shows the relative change of 2021-2040 and 2061-2080 to 1981-2000, respectively. The green lines represent the fixed bottom wind farms and floating wind farms in UK offshore area. The data include all pre-planning, planning, construction, and operational phases.

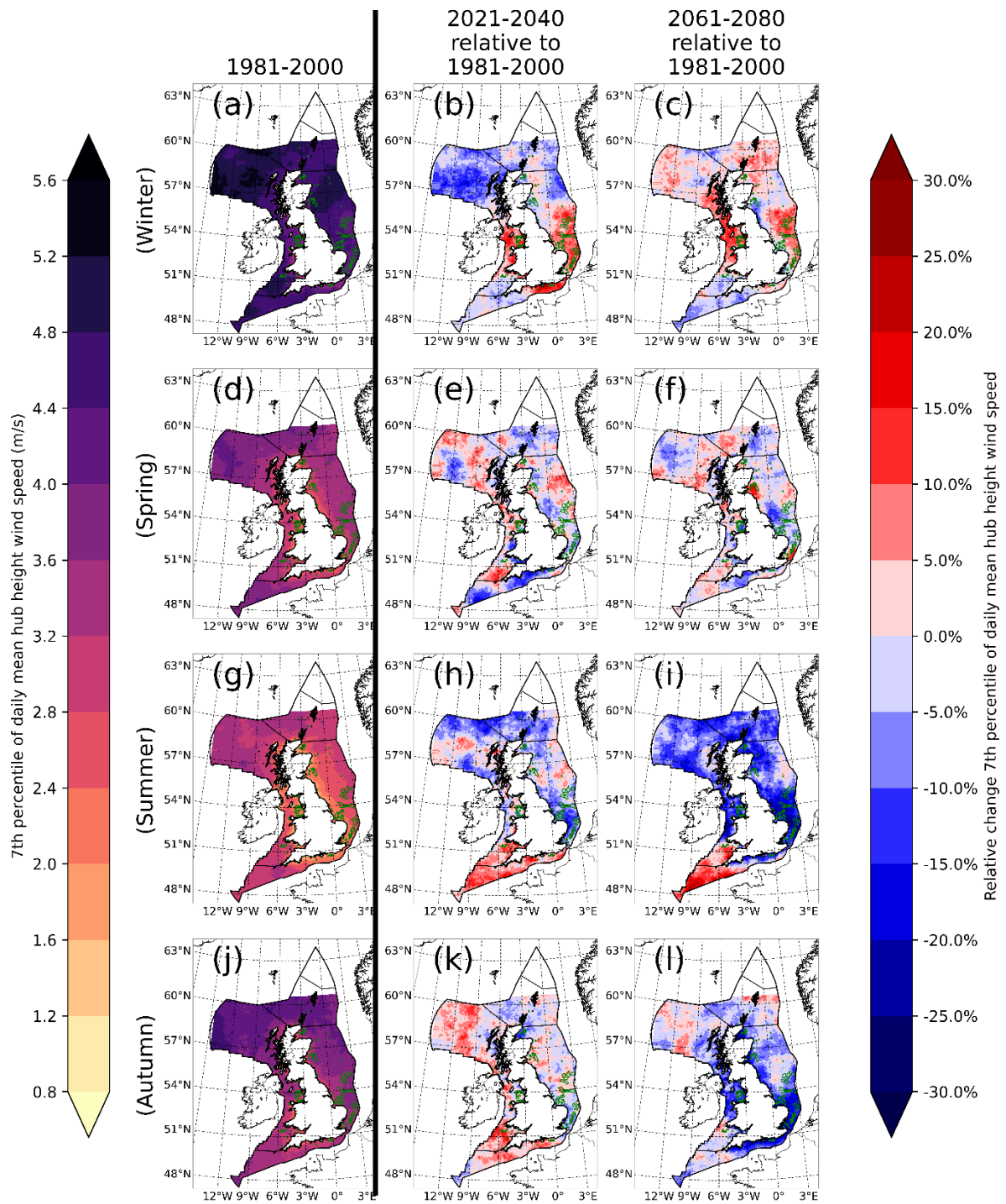


Figure A.3. Column one from left side 7th percentile of daily mean hub height wind speed in the four seasons for the 1981-2000 scenario. Rows from 1 to 4 represent the seasons: winter, spring, summer, and autumn. Column 2 and 3 from the left side shows the relative change of 2021-2040 and 2061-2080 to 1981-2000, respectively. The green lines represent the fixed bottom wind farms and floating wind farms in UK offshore area. The data include all pre-planning, planning, construction, and operational phases.

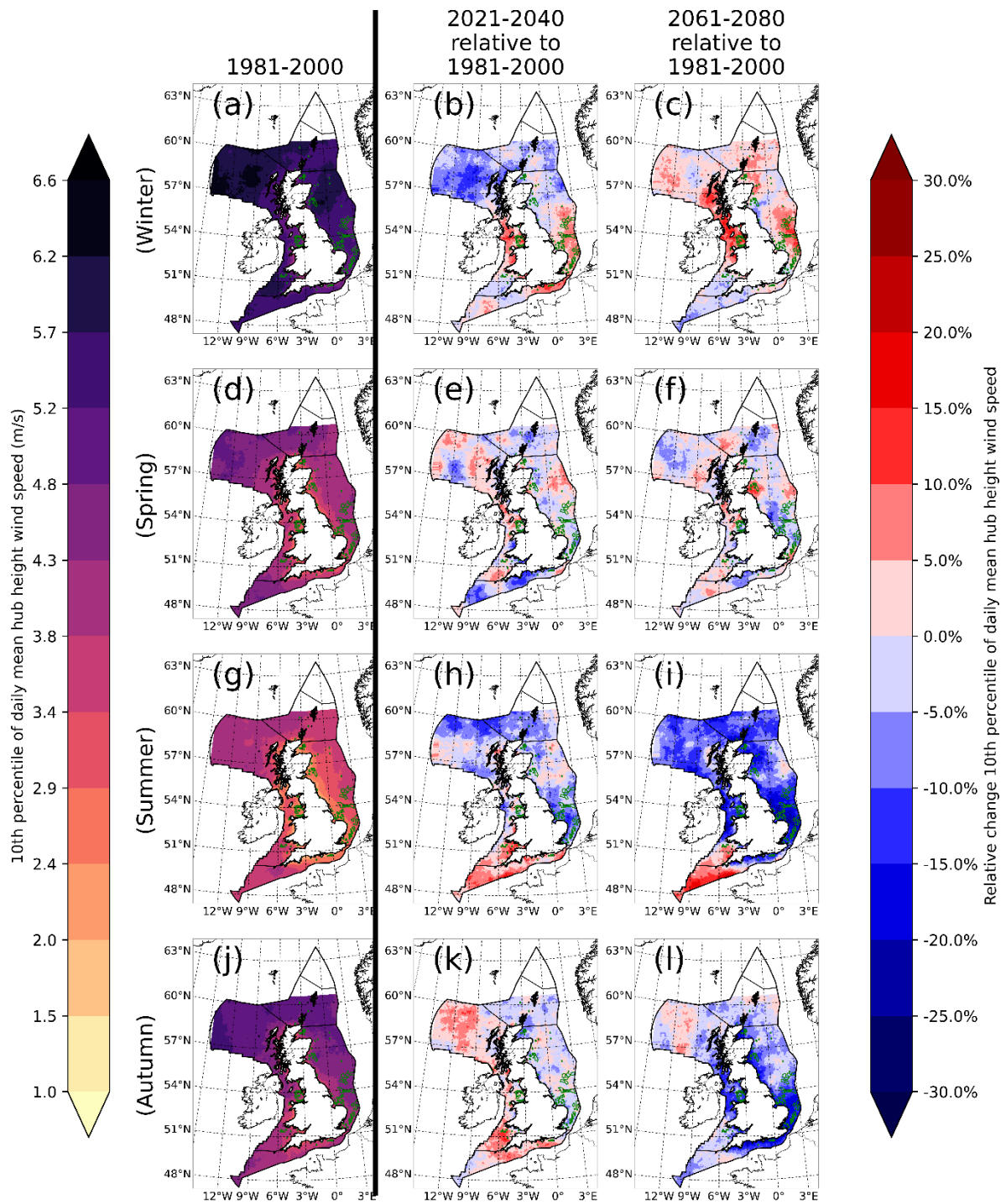


Figure A.4. Column one from left side 10th percentile of daily mean hub height wind speed in the four seasons for the 1981-2000 scenario. Rows from 1 to 4 represent the seasons: winter, spring, summer, and autumn. Column 2 and 3 from the left side shows the relative change of 2021-2040 and 2061-2080 to 1981-2000, respectively. The green lines represent the fixed bottom wind farms and floating wind farms in UK offshore area. The data include all pre-planning, planning, construction, and operational phases.

Appendix B: AHP for standardising weights

The Analytic hierarchy process (AHP) for weighting factors was used. AHP, first introduced by Saaty in 1980 [167], [168], assigns weights to standardised factor values according to their importance determined by a pairwise comparison method [38]. In this case the identified ten criteria of the problem are used in the pairwise comparison technique to assess their importance. The requisite pairwise comparison matrix is constructed to possess an equivalent number of rows and columns, aligning with the total number of factors under consideration. The value assigned to each element within the matrix corresponds to the Importance Index value as delineated in Table B.1, which is used to compare the factors pairs.

Table B.1. The Importance Index (I) scale [170].

Importance Index I	Definition	Description
1	Equal importance	Two activities contribute equally to the objective.
2	Intermediate value	
3	Moderate importance	Experience and judgment slightly favour one activity over another.
4	Intermediate value	
5	Strong importance	Experience and judgment strongly favour one activity over another.
6	Intermediate value	
7	Very strong	An activity is favoured very strongly over another.
8	Intermediate value	
9	Extreme importance	Evidence favouring one activity over another is of the highest possible order.

To map the participants weighting values from the range of 0 to 100 to the corresponding AHP Importance Index, we have used an equal range of values between 0 and 100 as a reference scale, see Table B.2. For example, when constructing the comparison table

for Participant 1 (see Table B.3), if the difference between CF (in left column) and WPD (in the top row) is 40, we insert 5, which is the corresponding AHP value. Table B.3 shows the pairwise comparison for Participant 1, a 10*10 matrix with a diagonal equal to 1, indicating equal importance between criteria. In Table B.4 - Table B.12, we have the pairwise comparison for Participants 2 to 10.

The assignment of the important index in the matrix is governed by the stipulation that the factor denoted in the leftmost column of the matrix (Table B.3) is deemed to hold superior significance in relation to the factor designated in the matrix's topmost row (Table B.3). For example, the value assigned to the cell intersecting CF in the leftmost to COV in the topmost (cell is highlighted in blue in Table B.3) is 4 because Participant 1 from Table 2.1 has assigned 40 to CF and 10 to COV. The difference between the two percentages is 30, corresponding to the AHP scale 4 (see Table B.2). Conversely, if the factor named in the left column of the matrix is assessed to have inferior importance when contrasted with the factor named in the matrix's top row (Table B.3), the matrix element is then computed as the reciprocal of the values articulated in Table B.1. For example, the value assigned to the cell intersecting WPD in the leftmost to CF in the topmost (cell is highlighted in green in Table B.3) is 1/5 because Participant 1 from Table 2.1 has assigned 0 to WPD and 40 to CF. The difference between the two percentages is 40, corresponding to the AHP scale 5 (see Table B.2). Since WPD is in the leftmost of the matrix and is inferior to CF, situated in the topmost, the assigned value in the green cell will be the reciprocal of 5.

Table B.2. Range of differences in participants weighting and the corresponding AHP scale.

Equal differences up to 100%	10	20	30	40	50	60	70	80	90	100
Range of the differences	<19		20-29	30-39	40-49	50-59	60-69	70-79	80-100	
AHP scale	2		3	4	5	6	7	8	9	

Table B.3. Pairwise comparison matrix for Participant 1 (P1).

P1	WPD	CF	COV	MV	SV	35m/s	50YEAR	low wind	DC	WD
WPD	1	1/5	1/2	1	1/2	1	1/2	1/2	1/2	1/2
CF	5	1	4	5	4	5	4	4	4	4
COV	2	1/4	1	2	1	2	1	1	1	1
MV	1	1/5	1/2	1	1/2	1	1/2	1/2	1/2	1/2
SV	2	1/4	1	2	1	2	1	1	1	1
35m/s	1	1/5	1/2	1	1/2	1	1/2	1/2	1/2	1/2
50YEAR	2	1/4	1	2	1	2	1	1	1	1
low wind	2	1/4	1	2	1	2	1	1	1	1
DC	2	1/4	1	2	1	2	1	1	1	1
WD	2	1/4	1	2	1	2	1	1	1	1

Table B.4. Pairwise comparison matrix for Participant 2 (P2).

P2	WPD	CF	COV	MV	SV	35m/s	50YEAR	low wind	DC	WD
WPD	1	1	2	3	3	3	3	3	3	3
CF	1	1	2	3	3	3	3	3	3	3
COV	1/2	1/2	1	2	2	2	2	2	2	2
MV	1/3	1/3	1/2	1	1/2	1	1	1	1/2	1/2
SV	1/3	1/3	1/2	2	1	2	2	2	2	1
35m/s	1/3	1/3	1/2	1	1/2	1	1	1	1/2	1/2
50YEAR	1/3	1/3	1/2	1	1/2	1	1	1	1/2	1/2
low wind	1/3	1/3	1/2	1	1/2	1	1	1	1/2	1/2
DC	1/3	1/3	1/2	2	1/2	2	2	2	1	1/2
WD	1/3	1/3	1/2	2	1	2	2	2	2	1

Table B.5. Pairwise comparison matrix for Participant 3 (P3).

P3	WPD	CF	COV	MV	SV	35m/s	50YEAR	low wind	DC	WD
WPD	1	1	1	1/2	1/3	1/2	1/2	1/2	1	1
CF	1	1	1	1/2	1/3	1/2	1/2	1/2	1	1
COV	1	1	1	1/2	1/3	1/2	1/2	1/2	1	1
MV	2	2	2	1	1/2	2	1	2	2	2
SV	3	3	3	2	1	2	2	2	2	2
35m/s	2	2	2	1/2	1/2	1	1/2	1	2	2
50YEAR	2	2	2	1	1/2	2	1	2	2	2
low wind	2	2	2	1/2	1/2	1	1/2	1	2	1
DC	1	1	1	1/2	1/3	1/2	1/2	1/2	1	1
WD	1	1	1	1/2	1/3	1/2	1/2	1/2	1	1

Table B.6. Pairwise comparison matrix for Participant 4 (P4).

P4	WPD	CF	COV	MV	SV	35m/s	50YEAR	low wind	DC	WD
WPD	1	1	2	2	2	1/2	2	2	2	2
CF	1	1	2	2	2	1/2	2	2	2	2
COV	1/2	1/2	1	1	1	1/2	2	2	2	2
MV	1/2	1/2	1	1	1	1/2	2	2	2	2
SV	1/2	1/2	1	1	1	1/2	2	2	2	2
35m/s	2	2	2	2	2	1	2	2	2	2
50YEAR	1/2	1/2	1/2	1/2	1/2	1/2	1	1	2	2
low wind	1/2	1/2	1/2	1/2	1/2	1/2	1	1	2	2
DC	1/2	1/2	1/2	1/2	1/2	1/2	1/2	1/2	1	1
WD	1/2	1/2	1/2	1/2	1/2	1/2	1/2	1/2	1	1

Table B.7. Pairwise comparison matrix for Participant 5 (P5).

P5	WPD	CF	COV	MV	SV	35m/s	50YEAR	low wind	DC	WD
WPD	1	1/4	2	2	1/2	1/2	1	1/2	2	2
CF	4	1	4	4	3	4	4	4	4	4
COV	1/2	1/4	1	1	1/2	1/2	1/2	1/2	1	1
MV	1/2	1/4	1	1	1/2	1/2	1/2	1/2	1	1
SV	2	1/3	2	2	1	2	2	2	2	2
35m/s	2	1/4	2	2	1/2	1	2	1	2	2
50YEAR	1	1/4	2	2	1/2	1/2	1	1/2	2	2
low wind	2	1/4	2	2	1/2	1	2	1	2	2
DC	1/2	1/4	1	1	1/2	1/2	1/2	1/2	1	1
WD	1/2	1/4	1	1	1/2	1/2	1/2	1/2	1	1

Table B.8. Pairwise comparison matrix for Participant 6 (P6).

P6	WPD	CF	COV	MV	SV	35m/s	50YEAR	low wind	DC	WD
WPD	1	1	2	2	2	2	2	2	1	1
CF	1	1	2	2	2	2	2	2	1	1
COV	1/2	1/2	1	1	1	1	1/2	1	1/2	1/2
MV	1/2	1/2	1	1	1	1	1/2	1	1/2	1/2
SV	1/2	1/2	1	1	1	1	1/2	1	1/2	1/2
35m/s	1/2	1/2	1	1	1	1	1/2	1	1/2	1/2
50YEAR	1/2	1/2	2	2	2	2	1	2	1/2	1/2
low wind	1/2	1/2	1	1	1	1	1/2	1	1/2	1/2
DC	1	1	2	2	2	2	2	2	1	1
WD	1	1	2	2	2	2	2	2	1	1

Table B.9. Pairwise comparison matrix for Participant 7 (P7).

P7	WPD	CF	COV	MV	SV	35m/s	50YEAR	low wind	DC	WD
WPD	1	1	2	1/2	1/2	2	1	1/2	2	2
CF	1	1	2	1/2	1/2	2	1	1/2	2	2
COV	1/2	1/2	1	1/2	1/2	2	1/2	1/2	2	2
MV	2	2	2	1	1/2	2	2	1	2	2
SV	2	2	2	2	1	2	2	2	2	2
35m/s	1/2	1/2	1/2	1/2	1/2	1	1/2	1/2	1/2	2
50YEAR	1	1	2	1/2	1/2	2	1	1/2	2	2
low wind	2	2	2	1	1/2	2	2	1	2	2
DC	1/2	1/2	1/2	1/2	1/2	2	1/2	1/2	1	2
WD	1/2	1/2	1/2	1/2	1/2	1/2	1/2	1/2	1/2	1

Table B.10. Pairwise comparison matrix for Participant 8 (P8).

P8	WPD	CF	COV	MV	SV	35m/s	50YEAR	low wind	DC	WD
WPD	1	1	2	2	2	2	2	3	2	2
CF	1	1	2	2	2	2	2	3	2	2
COV	1/2	1/2	1	2	2	2	2	2	2	2
MV	1/2	1/2	1/2	1	1	1	2	2	2	2
SV	1/2	1/2	1/2	1	1	1	2	2	2	2
35m/s	1/2	1/2	1/2	1	1	1	2	2	2	2
50YEAR	1/2	1/2	1/2	1/2	1/2	1/2	1	2	1	1
low wind	1/3	1/3	1/2	1/2	1/2	1/2	1/2	1	1/2	1/2
DC	1/2	1/2	1/2	1/2	1/2	1/2	1	2	1	1
WD	1/2	1/2	1/2	1/2	1/2	1/2	1	2	1	1

Table B.11. Pairwise comparison matrix for Participant 9 (P9).

P9	WPD	CF	COV	MV	SV	35m/s	50YEAR	low wind	DC	WD
WPD	1	1/2	1/2	1/2	2	2	1	1/2	2	2
CF	2	1	1	1	2	2	2	1	2	2
COV	2	1	1	1	2	2	2	1	2	2
MV	2	1	1	1	2	2	2	1	2	2
SV	1/2	1/2	1/2	1/2	1	1	1/2	1/2	1	1
35m/s	1/2	1/2	1/2	1/2	1	1	1/2	1/2	1	1
50YEAR	1	1/2	1/2	1/2	2	2	1	1/2	2	2
low wind	2	1	1	1	2	2	2	1	2	2
DC	1/2	1/2	1/2	1/2	1	1	1/2	1/2	1	1
WD	1/2	1/2	1/2	1/2	1	1	1/2	1/2	1	1

Table B.12. Pairwise comparison matrix for Participant 10 (P10).

P10	WPD	CF	COV	MV	SV	35m/s	50YEAR	low wind	DC	WD
WPD	1	1/2	2	2	2	2	2	2	2	2
CF	2	1	3	3	3	2	3	3	3	3
COV	1/2	1/3	1	1	1/2	1/2	1/2	1/2	1	1
MV	1/2	1/3	1	1	1/2	1/2	1/2	1/2	1	1
SV	1/2	1/3	2	2	1	1/2	1	1	2	2
35m/s	1/2	1/2	2	2	2	1	2	2	2	2
50YEAR	1/2	1/3	2	2	1	1/2	1	1	2	2
low wind	1/2	1/3	2	2	1	1/2	1	1	2	2
DC	1/2	1/3	1	1	1/2	1/2	1/2	1/2	1	1
WD	1/2	1/3	1	1	1/2	1/2	1/2	1/2	1	1

After constructing the pairwise comparison, a normalised matrix is formulated from the comparison matrix by dividing each matrix element by the summation of its respective column.

In this normalisation process, the weight attributed to each factor is determined as the mean value of its respective row within the newly generated matrix. Notably, the collective sum of these factor weights equates to unity; see Table B.13 and Figure B.1 for the weights generated by the AHP process. Criteria 2 (Capacity factor) has the highest weighting, followed by Criteria 1 (WPD). On the other hand, criteria 9 (Distance to coast) and criteria 10 (Water depth) has the lowest weighting.

The culminating step in the comprehensive execution of the pairwise comparison methodology involves the validation of the underlying comparison assumptions through the utilisation of the following equations [170],

$$\text{Consistency Index (CI)} = \frac{\lambda_{max} - n}{n - 1} \quad (\text{B.1})$$

Where λ_{max} is the principal eigenvalue, which is equal to the product of the factor weight and the summation of its column in the pairwise matrix. n is the number of factors.

$$\text{Consistence ratio (CR)} = \frac{CI}{ratio\ index} \quad (\text{B.2})$$

A consistency ratio (CR) < 0.1 is required to validate the accuracy of the Importance Index. A ratio index (random consistency index) corresponding to 10 factors has been used and is equal to 1.49 [169]. The CR has been calculated for each of the 10 participants, and a CR < 10% has resulted for all weights provided by participants, see Table B.13. Column PM in Table B.13 represents the mean weights across the ten participants (P1 to P10).

Table B.13. AHP weights for the 10 participants. Consistency ratio (CR) is given to all participants. PM is the mean of all weight. Pink and blue highlights indicate each participant's maximum and minimum weighting values, respectively.

Participant s	Weights										
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	PM
CR	0.0054	0.0189	0.0010	0.0268	0.0990	0.0072	0.0327	0.0204	0.0115	0.0167	
1. WPD	0.0484	0.2019	0.0631	0.1406	0.1918	0.1420	0.0993	0.1667	0.0934	0.1458	0.1294
2. CF	0.3141	0.2019	0.0631	0.1406	0.2531	0.1420	0.0993	0.1667	0.1416	0.2225	0.1745
3. COV	0.0904	0.1234	0.0631	0.0994	0.0460	0.0662	0.0753	0.1300	0.1416	0.0568	0.0893
4. MV	0.0473	0.0531	0.1409	0.0994	0.0460	0.0662	0.1405	0.0985	0.1416	0.0568	0.0891
5. SV	0.0904	0.0924	0.1959	0.0994	0.1167	0.0662	0.1730	0.0985	0.0616	0.0923	0.1087
6. 35m/s	0.0473	0.0531	0.1068	0.1731	0.0921	0.0662	0.0570	0.0985	0.0616	0.1269	0.0883
7. 50YEAR	0.0904	0.0531	0.1409	0.0703	0.06981	0.1004	0.09938	0.0650	0.0934	0.0923	0.0875
8. low wind	0.0904	0.0531	0.0996	0.0703	0.09211	0.0662	0.14055	0.0454	0.1416	0.0923	0.0892
9. DC	0.0904	0.0751	0.0631	0.0532	0.04605	0.1420	0.06557	0.0650	0.0616	0.0568	0.0719
10. WD	0.0904	0.0924	0.0631	0.0532	0.04605	0.1420	0.04969	0.0650	0.0616	0.0568	0.0721

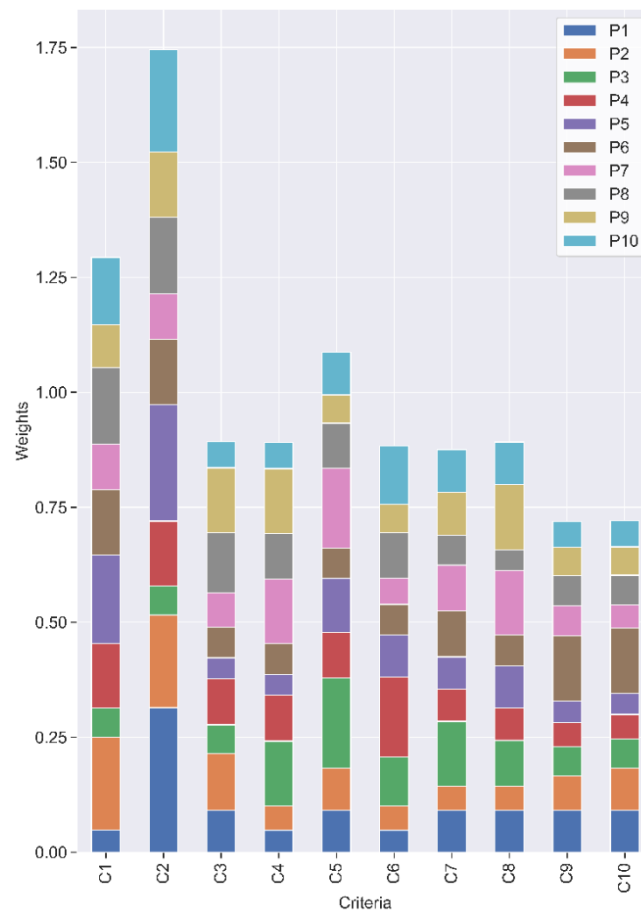


Figure B.1. The 10 Participants (P1 to P10) weighting for each of the ten criteria (C1 to C10).

❖ The below results are the corresponding for the results in sections 7.7 and 7.9.

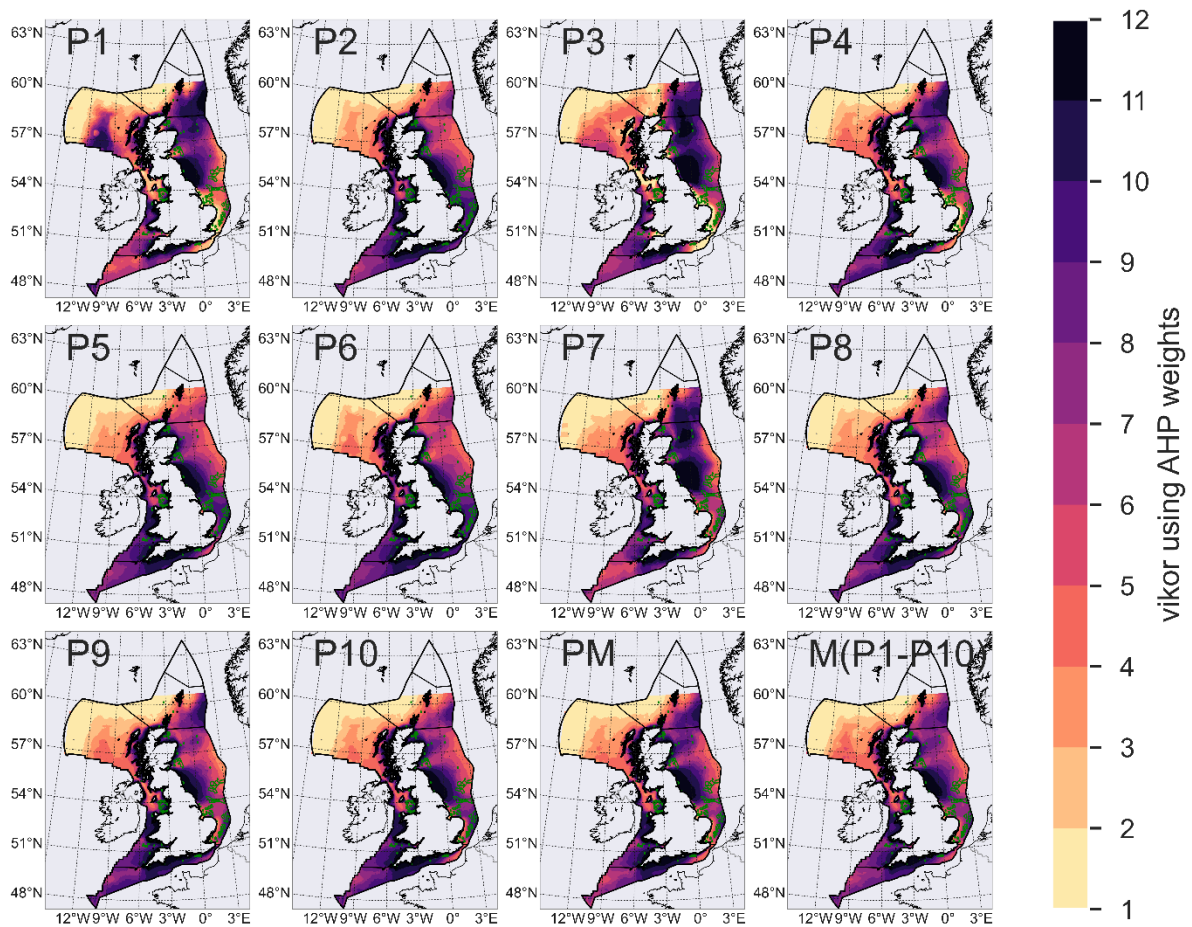


Figure B.2. The 12 ranking categories using the Vikor method in the baseline scenario. P1 to P10 represent the ranking corresponding to the weighting of each of the 10 participants. PM is the ranking using the mean of the AHP weights for Participants P1 to P10. M(P1-P10) is the mean of the final ranking in plots P1 to P10. This Figure is the corresponding for Figure 7.6.

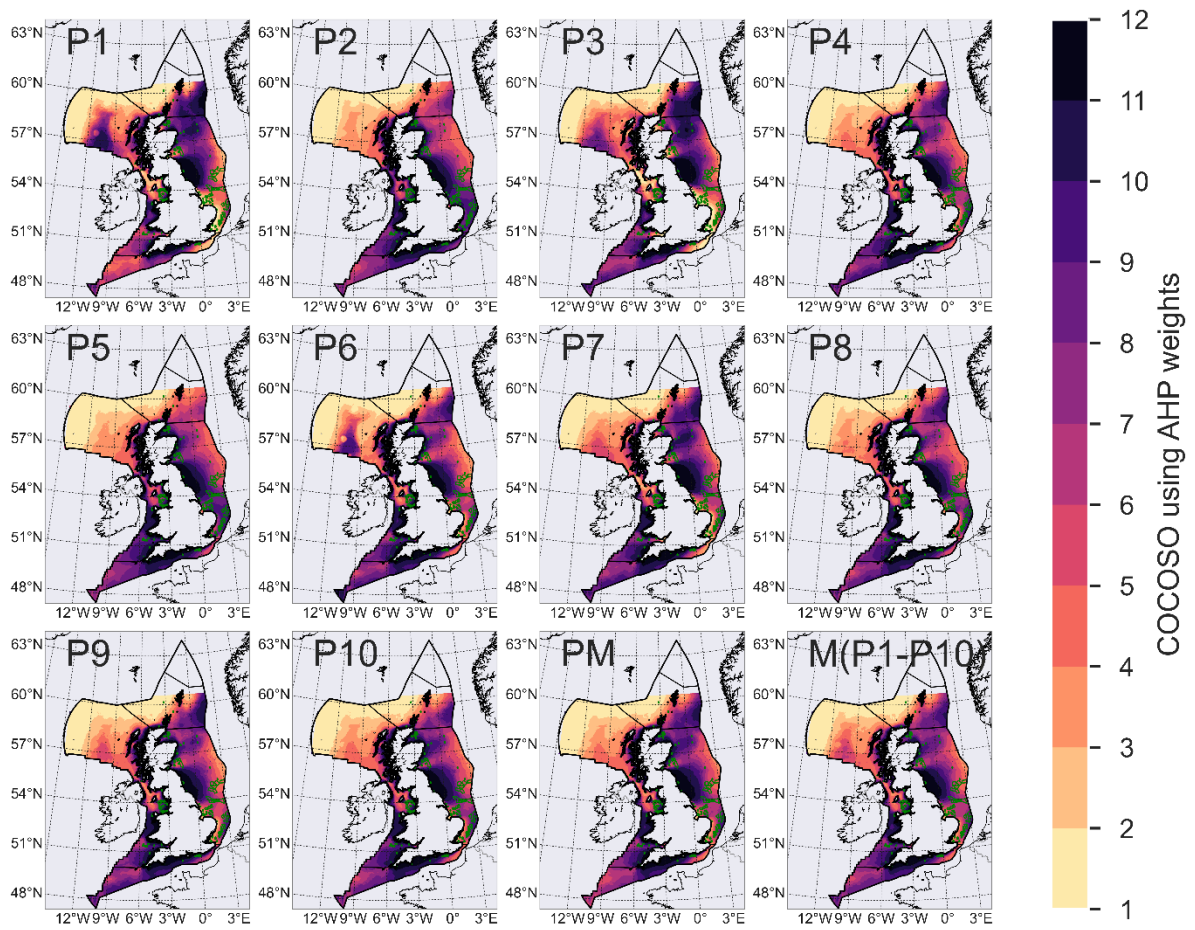


Figure B.3. The 12 ranking categories using the Cocoso method in the baseline scenario. P1 to P10 represent the ranking corresponding to the weighting of each of the 10 participants. PM is the ranking using the mean of the AHP weights for Participants P1 to P10. M(P1-P10) is the mean of the final ranking in plots P1 to P10. This Figure is the corresponding for Figure 7.7.

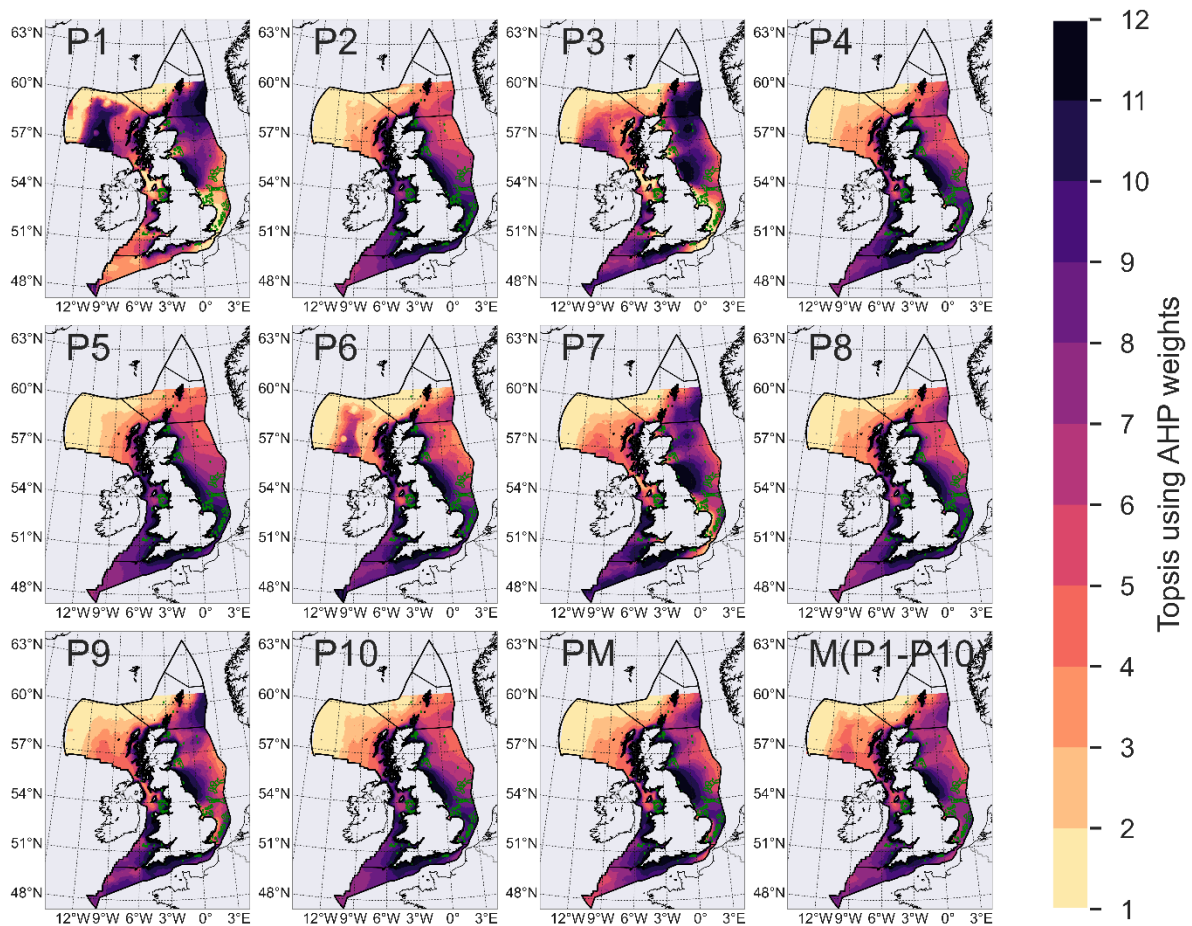


Figure B.4. The 12 ranking categories using the Topsis method in the baseline scenario. P1 to P10 represent the ranking corresponding to the weighting of each of the 10 participants. PM is the ranking using the mean of the AHP weights for Participants P1 to P10. M(P1-P10) is the mean of the final ranking in plots P1 to P10. This Figure is the corresponding for Figure 7.8.

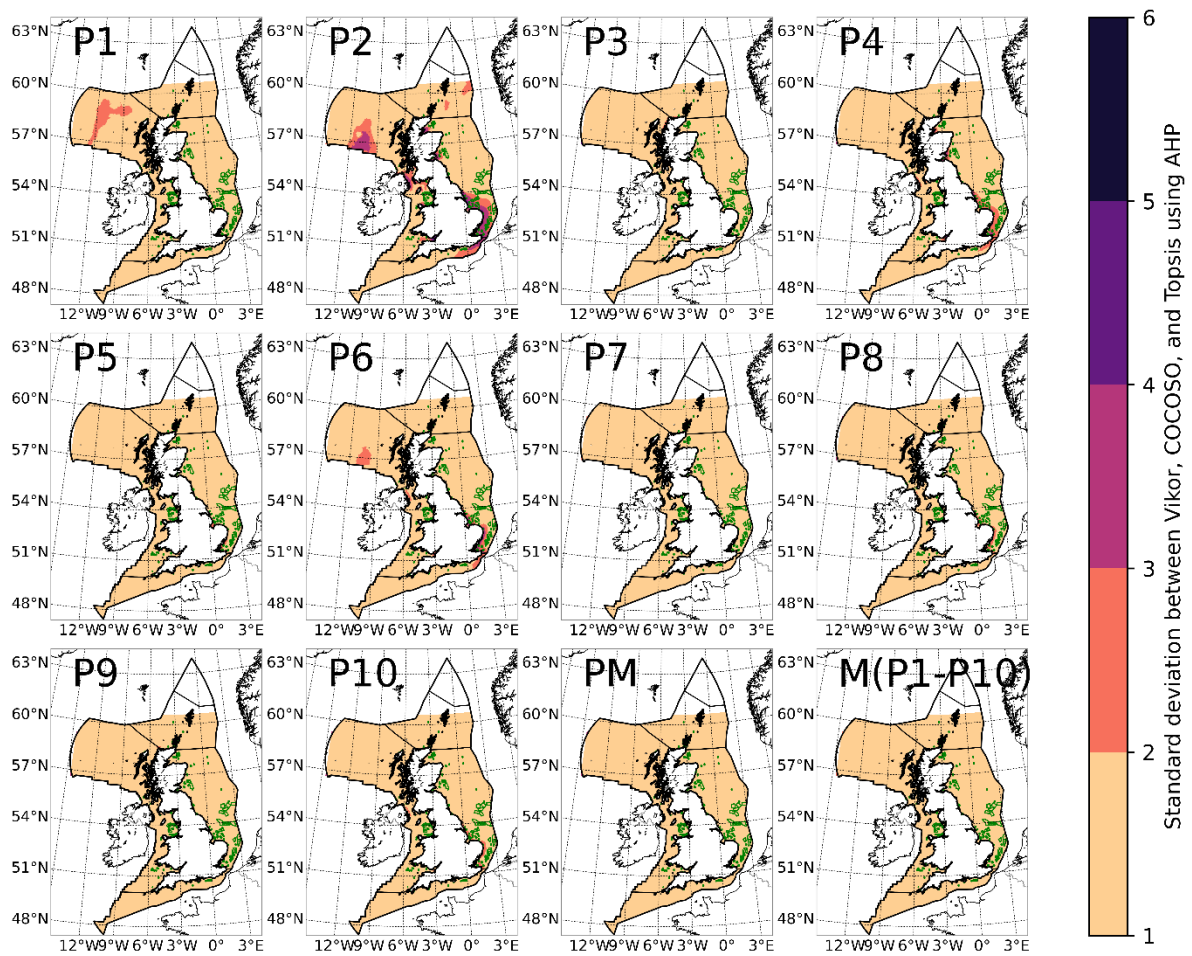


Figure B.5. The standard deviation between vikor , COCOSO, and topsis for each of the 10 participants in the baseline scenario. P1 to P10 represent the standard deviation corresponding to the weighting of each of the 10 participants. PM is the standard deviation using the mean of the normalised weights for Participants P1 to P10. M(P1-P10) is the mean of the final ranking in plots P1 to P10. This Figure is the corresponding for Figure 7.10.

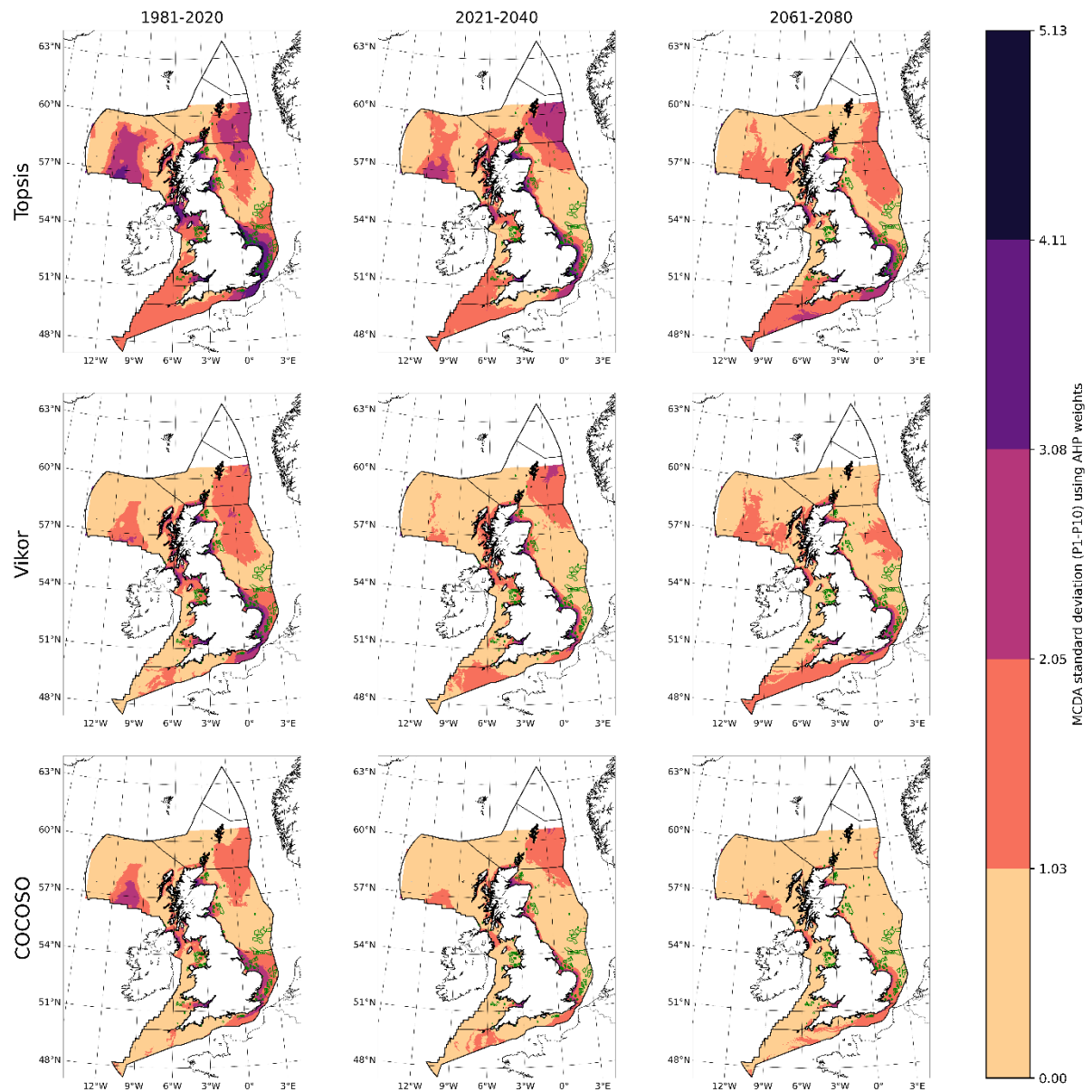


Figure B.6. Standard deviation for the ranking obtained from the ten participants (P1-P10) using AHP weights. Rows from 1 to 3 represent the three MCDA, Topsis, Vikor, and Cocoso, respectively, and column (a) shows the climate period 1981-2000, column (b) 2021-2040, and column (c) 2061-2080. Black outer boundaries represent the EEZ, and black internal boundaries represent four regions considered in the study. The green lines represent the fixed bottom wind farms and floating wind farms in UK offshore area. The data include all pre-planning, planning, construction, and operational phases. This Figure is the corresponding for Figure 7.9.

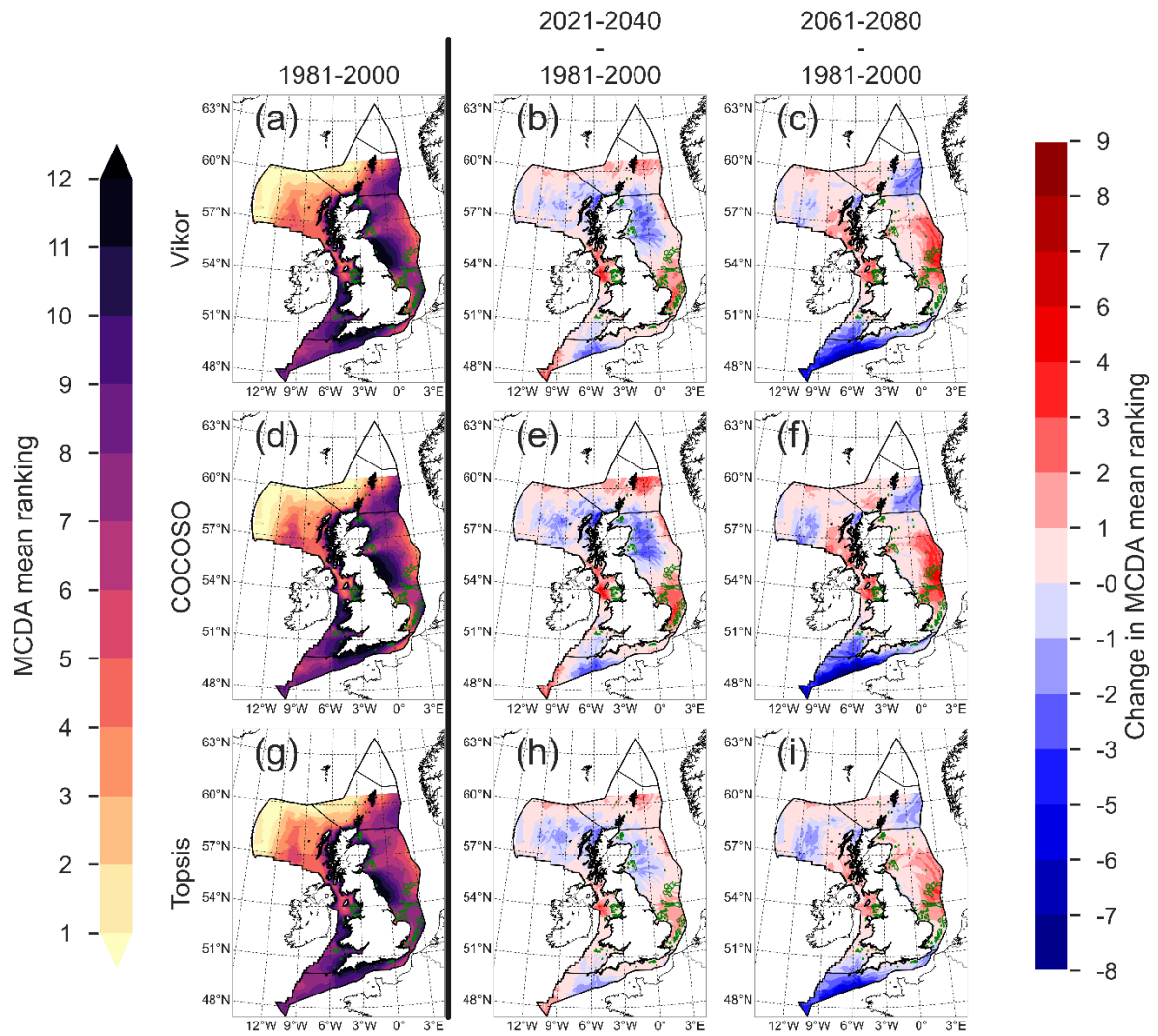


Figure B.7. Spatial map representing the 12 ranking category for the mean ranking MCDA methods, rows from 1 to 3 represent the three MCDA, Vikor, Cocoso, and Topsis, respectively, and column (a) shows the climate period 1981-2000, column (b) 2021-2040 - 1981-2000, and column (c) 2061-2080 - 1981-2000. Black outer boundaries represent the EEZ, and black internal boundaries represent four regions considered in the study. The green lines represent the fixed bottom wind farms and floating wind farms in UK offshore area. The data include all pre-planning, planning, construction, and operational phases. This Figure is the corresponding for Figure 7.15.

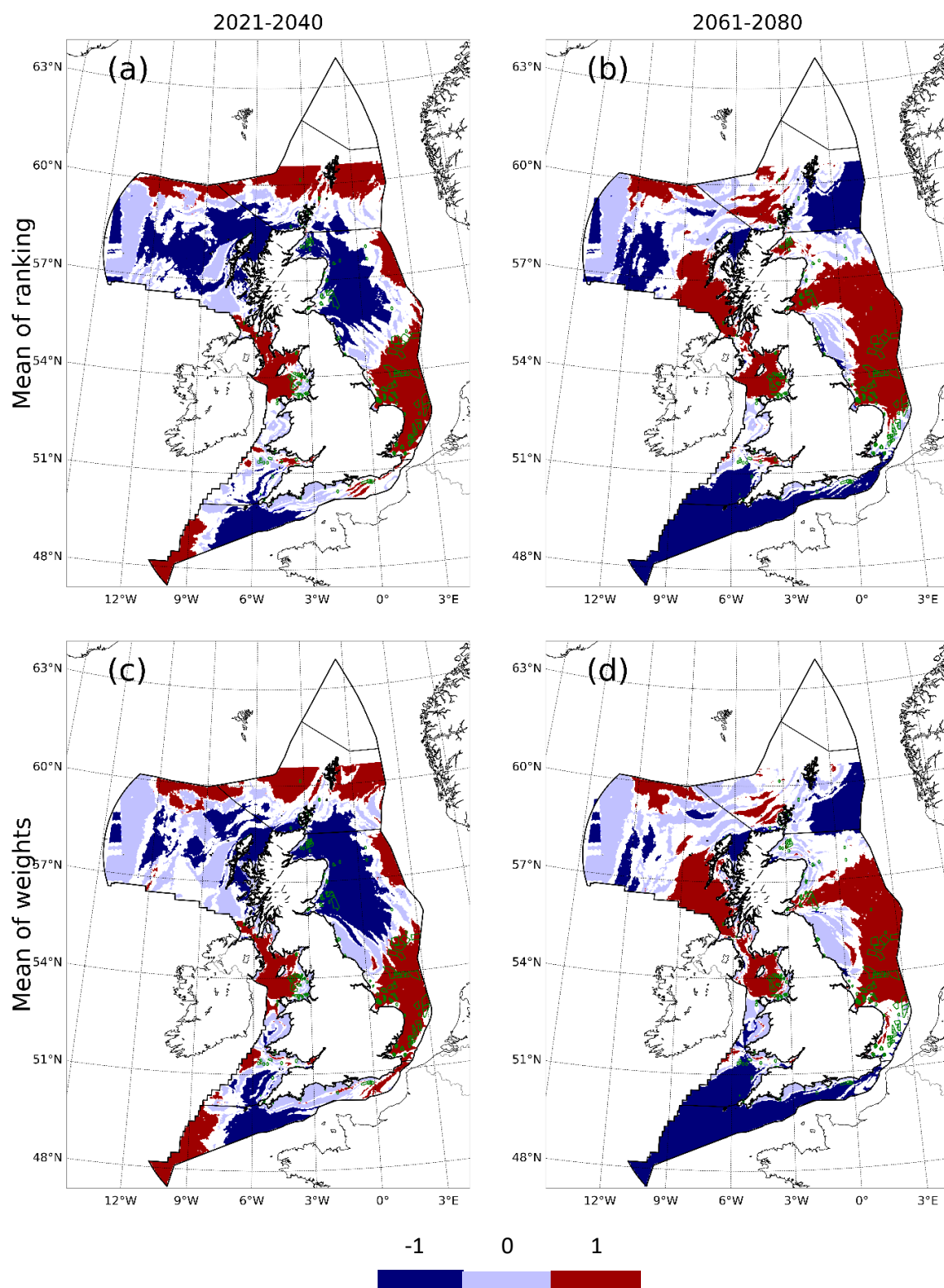


Figure B.8. Overlap of positive, negative, and no change between the mean of the ranking category (row 1) and the mean of the weights (row 2) for Vikor, Cocoso, and Topsis in 2021-2040 (column 1) and 2061-2080 (column 2). Dark blue holds the value of -1, indicating ranking decrease = more advantageous locations; light blue has a value of 0, meaning no change and red colour holds the value of 1, indicating ranking increase fewer advantageous locations. White colour locations inside the UK EEZ boundaries indicate no agreement between the three MCDAs. This Figure is the corresponding for Figure 7.16.

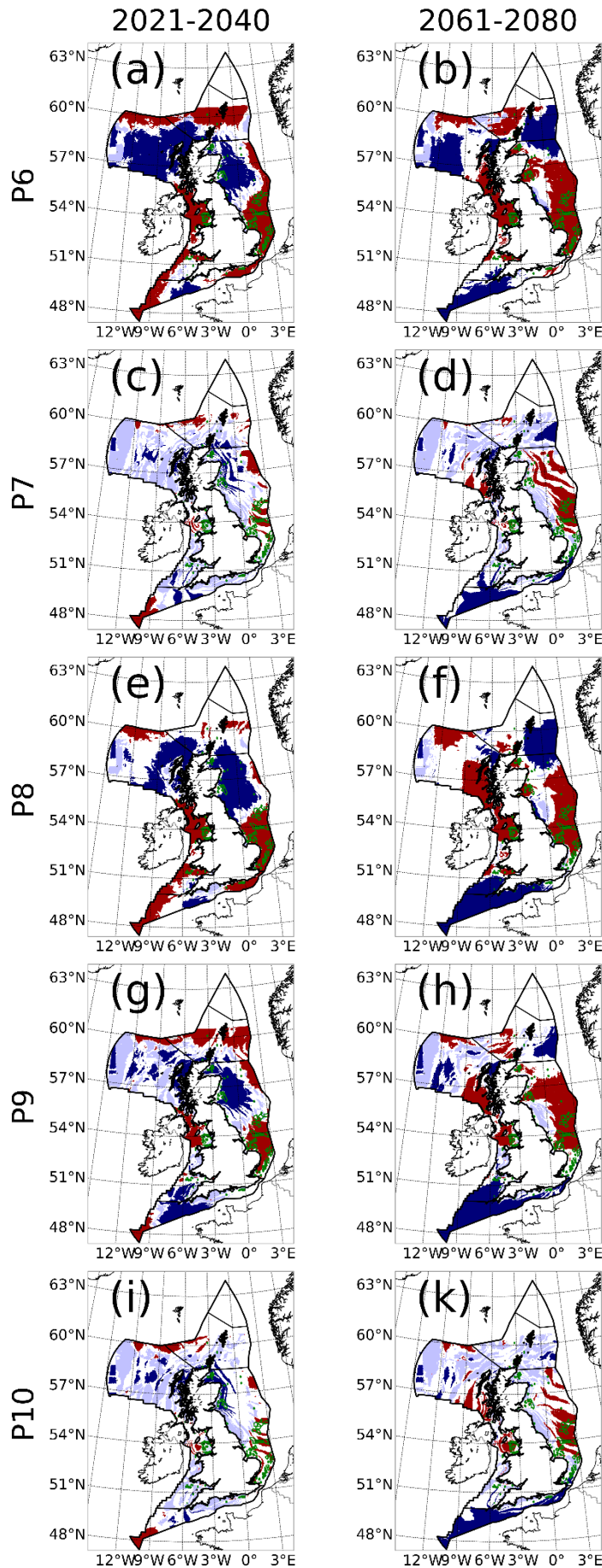


Figure B.9. Overlap of positive, negative, and no change between the mean of the weights of Vikor, Cocoso, and Topsis for first five Participants (P1 to P5). Left column show the changes in 2021-2040 and the right column show the changes in 2061-2080. Dark blue holds the value of -1, indicating locations with a decrease in the ranking across Vikor, Cocoso, and Topsis; light blue has a value of 0, meaning no change and red colour holds the value of 1, indicating an increase in ranking. White colour locations inside the UK EEZ boundaries indicate no agreement (positive, negative, or no change) between the three MCDAs. This Figure is the corresponding for Figure 7.17.

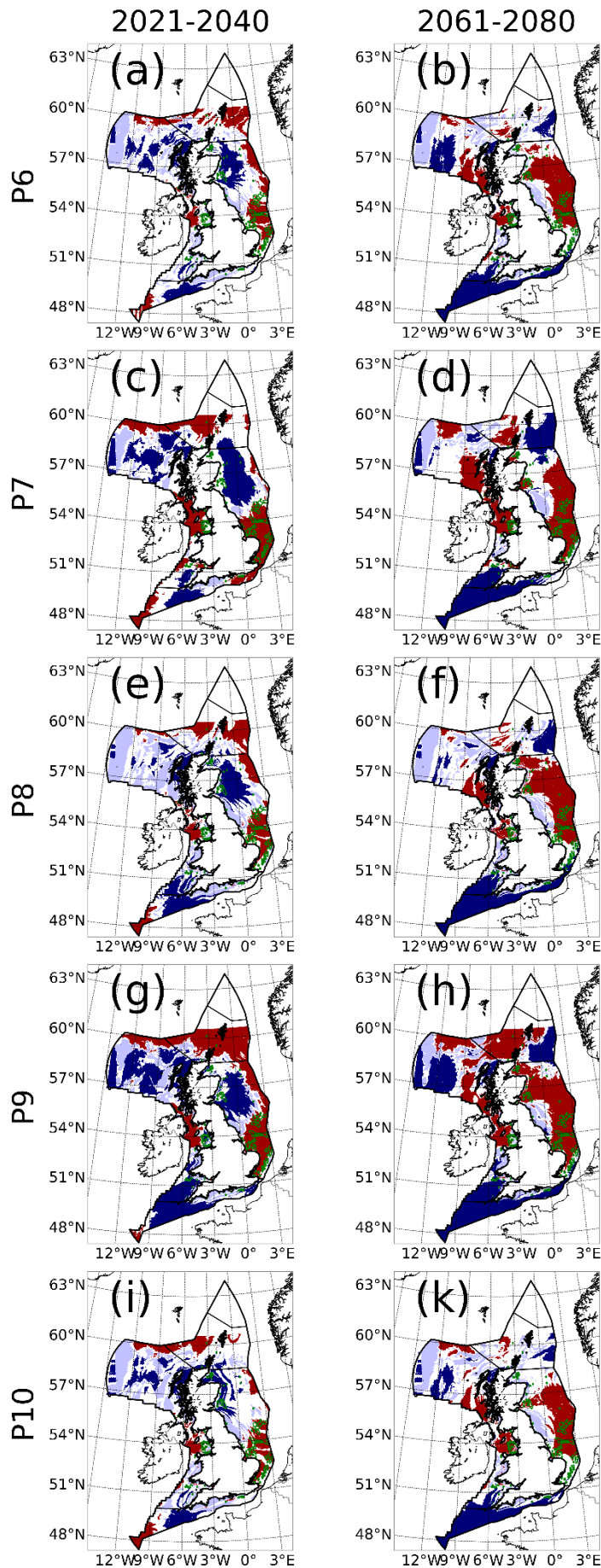


Figure B.10. Overlap of positive, negative, and no change between the mean of the weights of Vikor, Cocoso, and Topsis for second five Participants (P6 to P10). The left column shows the changes in 2021-2040, and the right column shows the changes in 2061-2080. Dark blue holds the value of -1, indicating locations with a decrease in the ranking across Vikor, Cocoso, and Topsis; light blue has a value of 0, meaning no change and red colour holds the value of 1, indicating an increase in ranking. White colour locations inside the UK EEZ boundaries indicate no agreement (positive, negative, or no change) between the three MCDAs. This Figure corresponds to Figure 7.18.

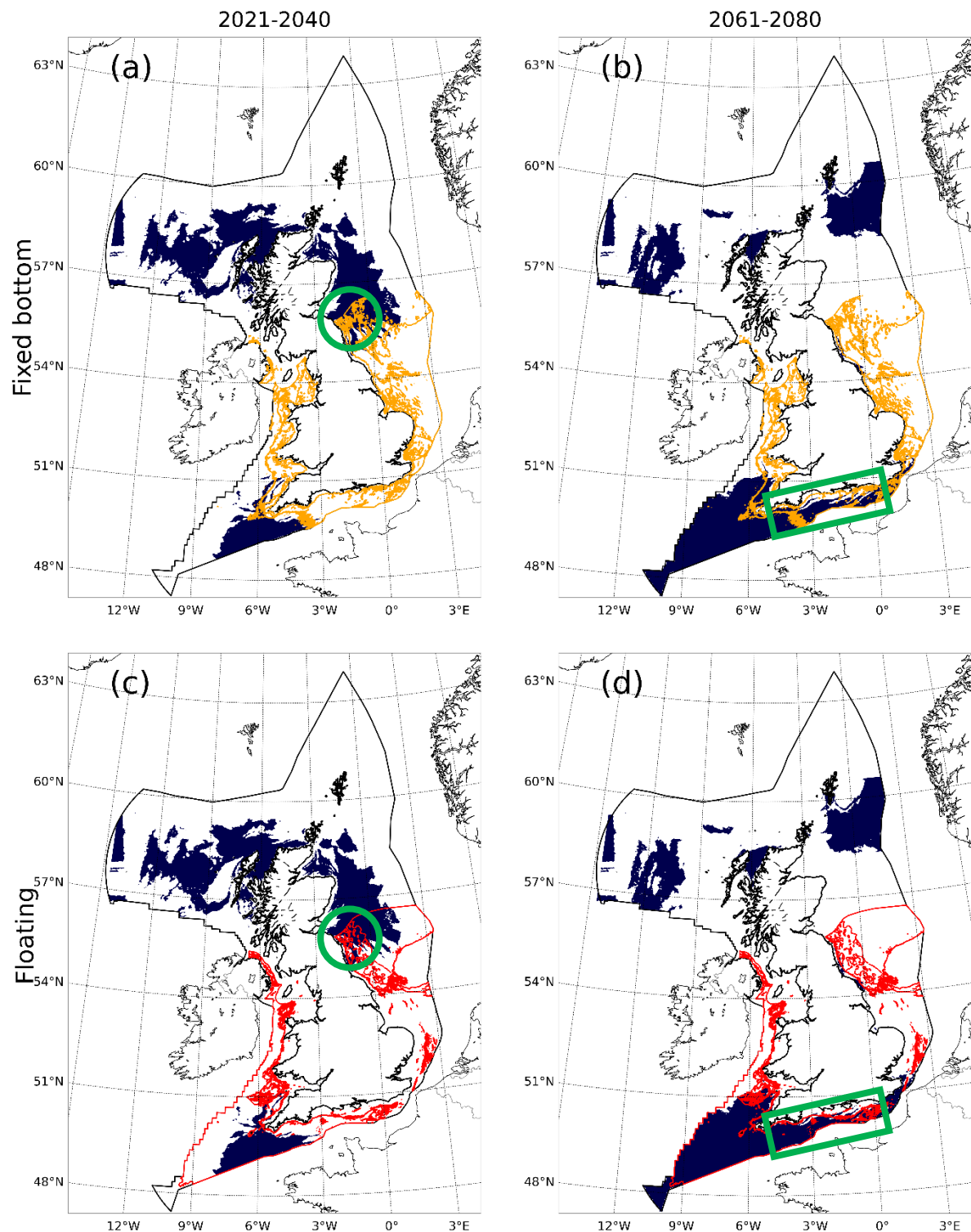


Figure B.11. Overlap of recommended locations (negative change in ranking category) for the mean of the ranking category ranking across Vikor, Cocomo, and Topsis in dark blue. In plots (a) and (b) boundaries of the crown estate fixed bottom substructure resources is in yellow lines and in plots (c) and (d) boundaries of the crown estate floating substructure resources is in red lines. Column 1 represent 2021-2040 and column 2 is the 2061-2080 period. The green highlighted areas indicate locations identified by the crown estate suitable for fixed bottom and floating installation simultaneously overlap our recommendation for future installations. This Figure is the corresponding for Figure 7.19.

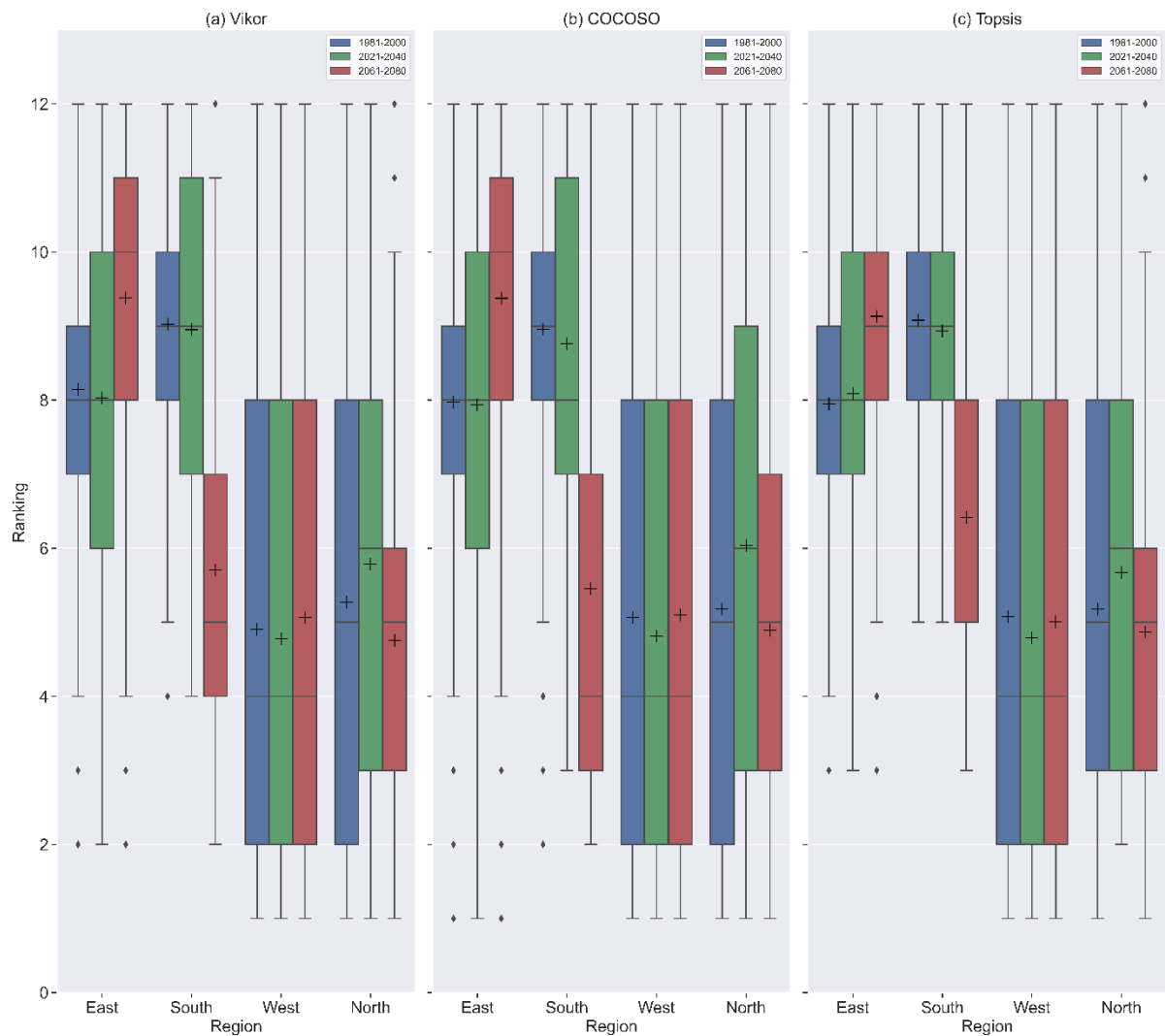


Figure B.12. Box plots show the 12 ranking categories for three periods (1981-2000 (blue), 2021-2040 (green), 2061-2080 (red)) among three MCDA methods, (a) Vikor, (b) Cocoso, and (c) Topsis. Each plot's four comparison panels for the four regions, East, South, West, and North. The box holds the interquartile ranges (IQR), the midline represents the median, and the plus marker represents the region mean. The thin vertical black line represents the rest of the distribution, except for points determined to be "outliers". The whiskers show the maximum and minimum values. The points beyond the thin vertical lines are outliers. This Figure is the corresponding for Figure 7.14.

Appendix C: Equal weights for MCDA

Figure C. 1 shows Kendall's Tau correlation between Vikor, Cocoso, and Topsis methods using equal weights for the ten participants ranking in the baseline period. The high value correlation between the Topsis and COCOSO methods is 0.95. On the other hand, it can be seen a significant decrease in Vikor correlation to the other two MCDA methods. Based on that the Vikor method will be excluded from the analysis of participants equal weights impact on ranking.

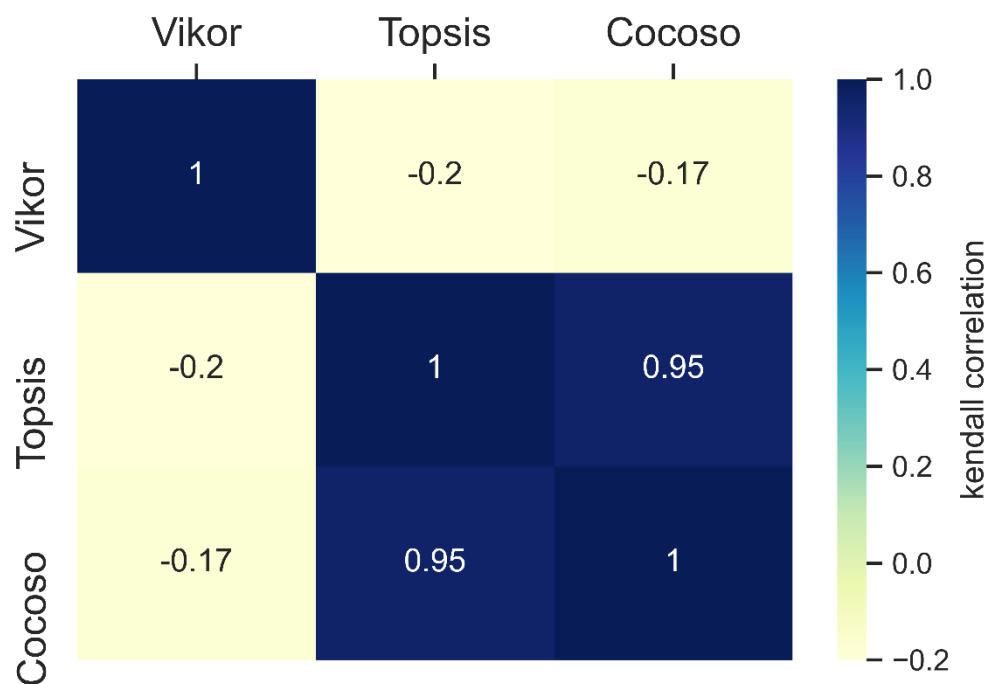


Figure C. 1. Kendall correlation between Vikor, Topsis, and Cocoso using equal weights for the 10 participants.

❖ The below results are the corresponding for the results in sections 7.7 and 7.9.

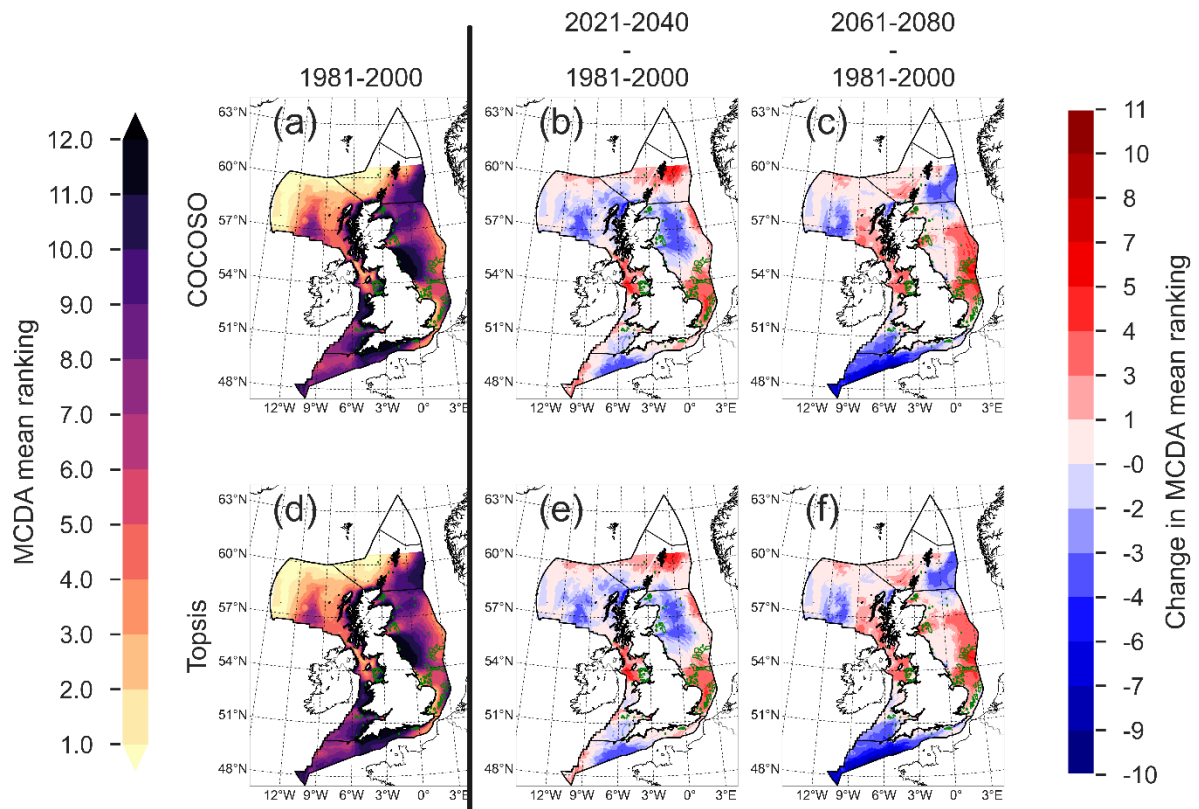


Figure C.2. Spatial map representing the 12 ranking category for the ranking of the MCDA methods using equal weights, rows from 1 and 2 represent the Cocoso, and Topsis methods, respectively, and column (a) shows the climate period 1981-2000, column (b) 2021-2040 - 1981-2000, and column (c) 2061-2080 - 1981-2000. Black outer boundaries represent the EEZ, and black internal boundaries represent four regions considered in the study. The green lines represent the fixed bottom wind farms and floating wind farms in UK offshore area. The data include all pre-planning, planning, construction, and operational phases. This Figure is the corresponding for Figure 7.15.

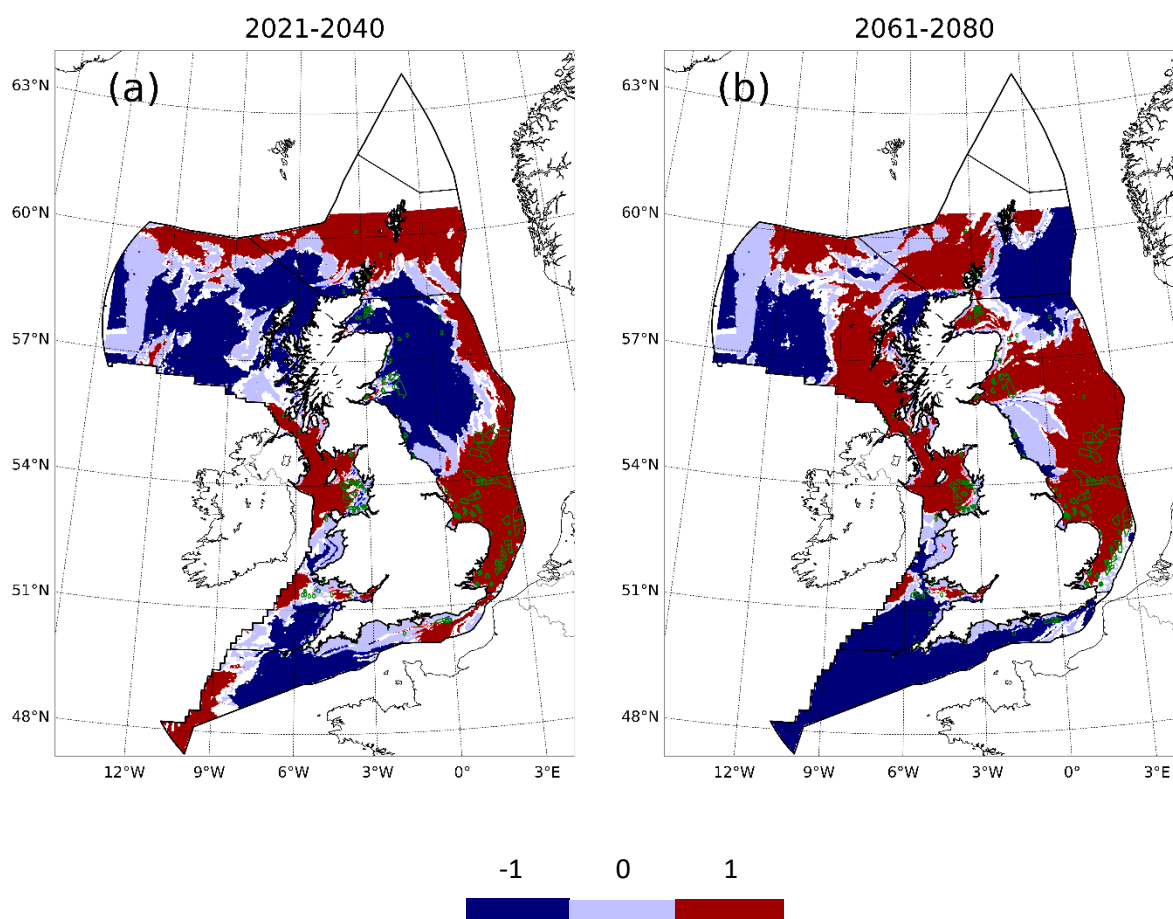


Figure C.3. Overlap of positive, negative, and no change between the ranking category using equal weights for Cocos, and Topsis in 2021-2040 (column 1) and 2061-2080 (column 2). Dark blue holds the value of -1, indicating ranking decrease = more advantageous locations; light blue has a value of 0, meaning no change and red colour holds the value of 1, indicating ranking increase fewer advantageous locations. White colour locations inside the UK EEZ boundaries indicate no agreement between the three MCDAs. This Figure is the corresponding for Figure 7.16.

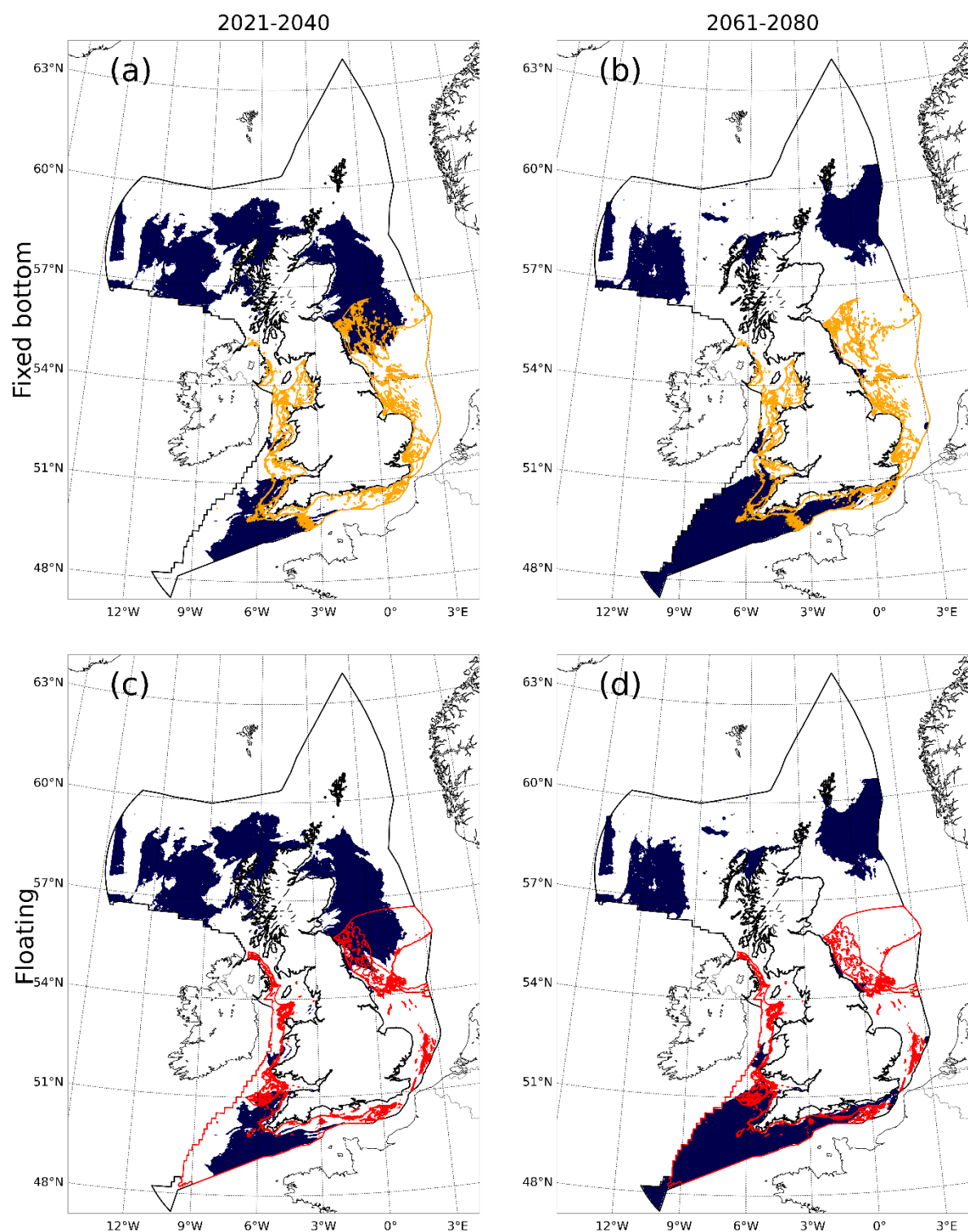


Figure C.4. Overlap of recommended locations (negative change in ranking category) for the ranking category ranking using equal weights across Cocoso, and Topsis in dark blue. In plots (a) and (b) boundaries of the crown estate fixed bottom substructure resources is in yellow lines and in plots (c) and (d) boundaries of the crown estate floating substructure resources is in red lines. Column 1 represent 2021-2040 and column 2 is the 2061-2080 period. The green highlighted areas indicate locations identified by the crown estate suitable for fixed bottom and floating installation simultaneously overlap our recommendation for future installations. This Figure is the corresponding for Figure 7.19.

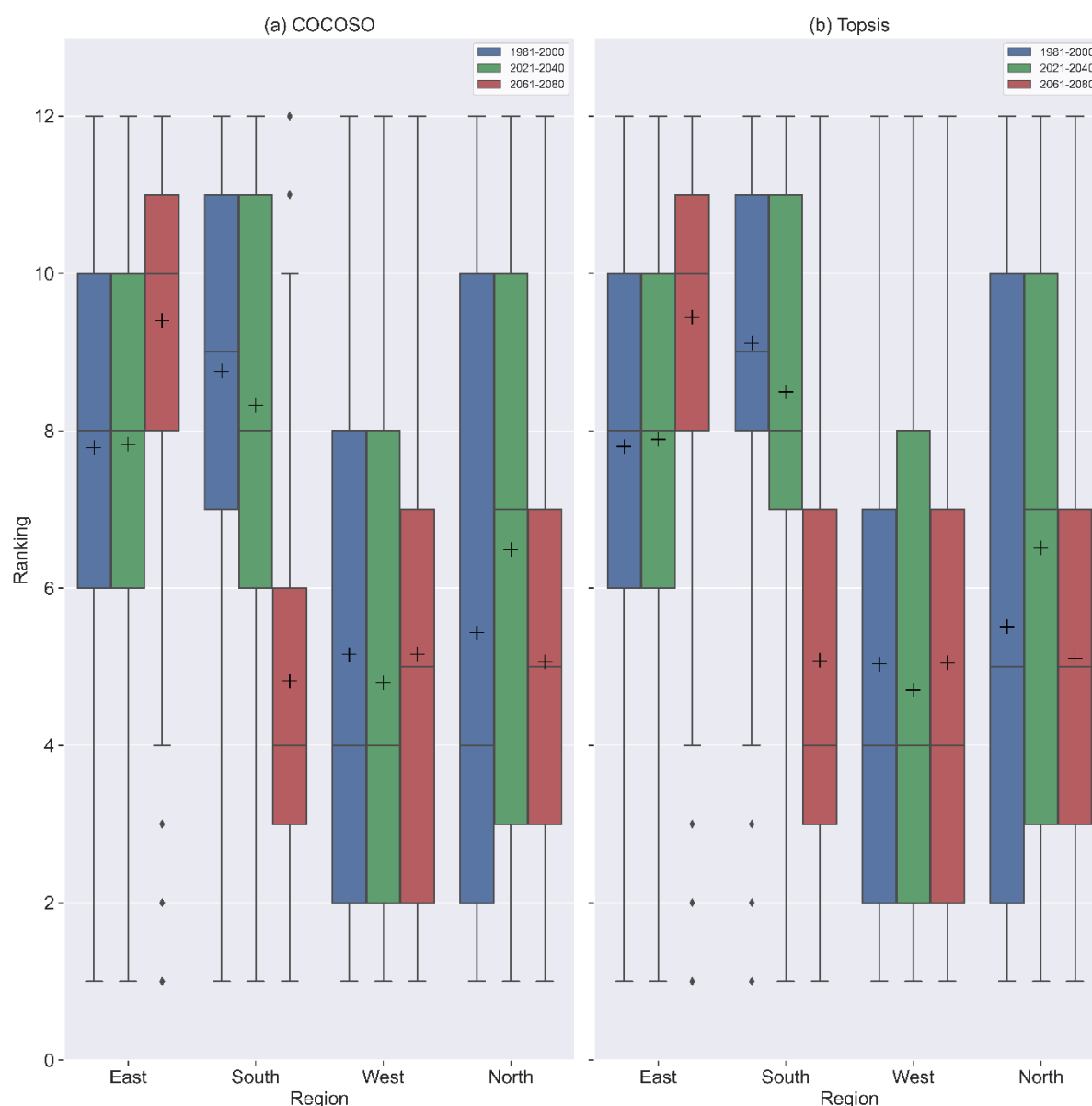


Figure C.5. Box plots show the 12 ranking categories for three periods (1981-2000 (blue), 2021-2040 (green), 2061-2080 (red)) for two MCDA methods, (a) Cocoso and (b) Topsis. Each plot's four comparison panels for the four regions, East, South, West, and North. The box holds the interquartile ranges (IQR), the midline represents the median, and the plus marker represents the region mean. The thin vertical black line represents the rest of the distribution, except for points determined to be “outliers”. The whiskers show the maximum and minimum values. The points beyond the thin vertical lines are outliers. This Figure is the corresponding for Figure 7.14.

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