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Geospatial dimensions of the renewable energy transition — The importance of prioritisation

Felix Butschek [a,b,c,1,*], Jared L. Peters [b,d,1], Tiny Remmers [b,e,f], Jimmy Murphy [b,g], Andrew J. Wheeler [a,b,c]

[a] School of Biological, Earth and Environmental Sciences, University College Cork, Distillery Fields, Cork, Ireland
[b] MaREI, the SFI Research Centre for Energy, Climate and Marine, University College Cork, Environmental Research Institute Beaufort Building, Ireland
[c] iCRAG, the SFI Centre for Research in Applied Geosciences, University College Cork, Ireland
[d] Green Rebel, Unit 1A, Penrose 1, Penrose Quay, Cork, Ireland
[e] College of Science and Engineering, James Cook University, Townsville, Queensland, 4811, Australia
[f] Australian Institute of Marine Science, Cape Cleveland, Queensland, 4811, Australia
[g] Department of Civil and Environmental Engineering, University College Cork, College Road, Cork, Ireland

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A B S T R A C T

The renewable energy transition is a priority for many researchers, policy makers, and political leaders because it is projected to stop the dependence of economic growth on increasing fossil fuel use and thus curtail climate change. This study examines how expert judgments affect development decisions to enable the renewable energy transition. Geospatial Multi-Criteria Decision Analyses (MCDA) are frequently used to select offshore wind energy (OWE) sites, however, they are often weak and/or often rely on limited judgement. The Analytical Hierarchy Process is used here with 25 diverse experts to assess the variability in priorities for OWE siting criteria. A geospatial MCDA is implemented using experts' individual priorities, aggregated weights and Monte Carlo simulations. Case study results reveal large variations in expert opinions and bias strongly affecting MCDAs weighted by single decision-makers. A group-decision approach is proposed to strengthen consent for OWE, underpinning the renewable energy transition.

1. Introduction

The flow of electrons is a defining characteristic of our modern society. In 2018, global electricity production totalled 26,619 TWh and 64.2% were supplied by relatively antiquated, "traditional" power sources such as oil, coal and natural gas (IEA, 2020a), which involve the environmentally untenable burning of fossil fuels. Changing this paradigm will require synergies between governments and energy production industries to develop infrastructure and establish policy changes. Academic research will likely be important for streamlining a transition to renewable energy with recent work suggesting there is some harmony between trends in industry and academia (Peters et al., 2020d). Thus, critical academic research is poised to help in transitioning energy production to renewable

Abbreviations: AHP, Analytical hierarchy process; MCDA, Multi-criteria decision analysis.

* Corresponding author.
E-mail address: felix.butschek@ucc.ie (F. Butschek).

[1] These authors contributed equally to this work.

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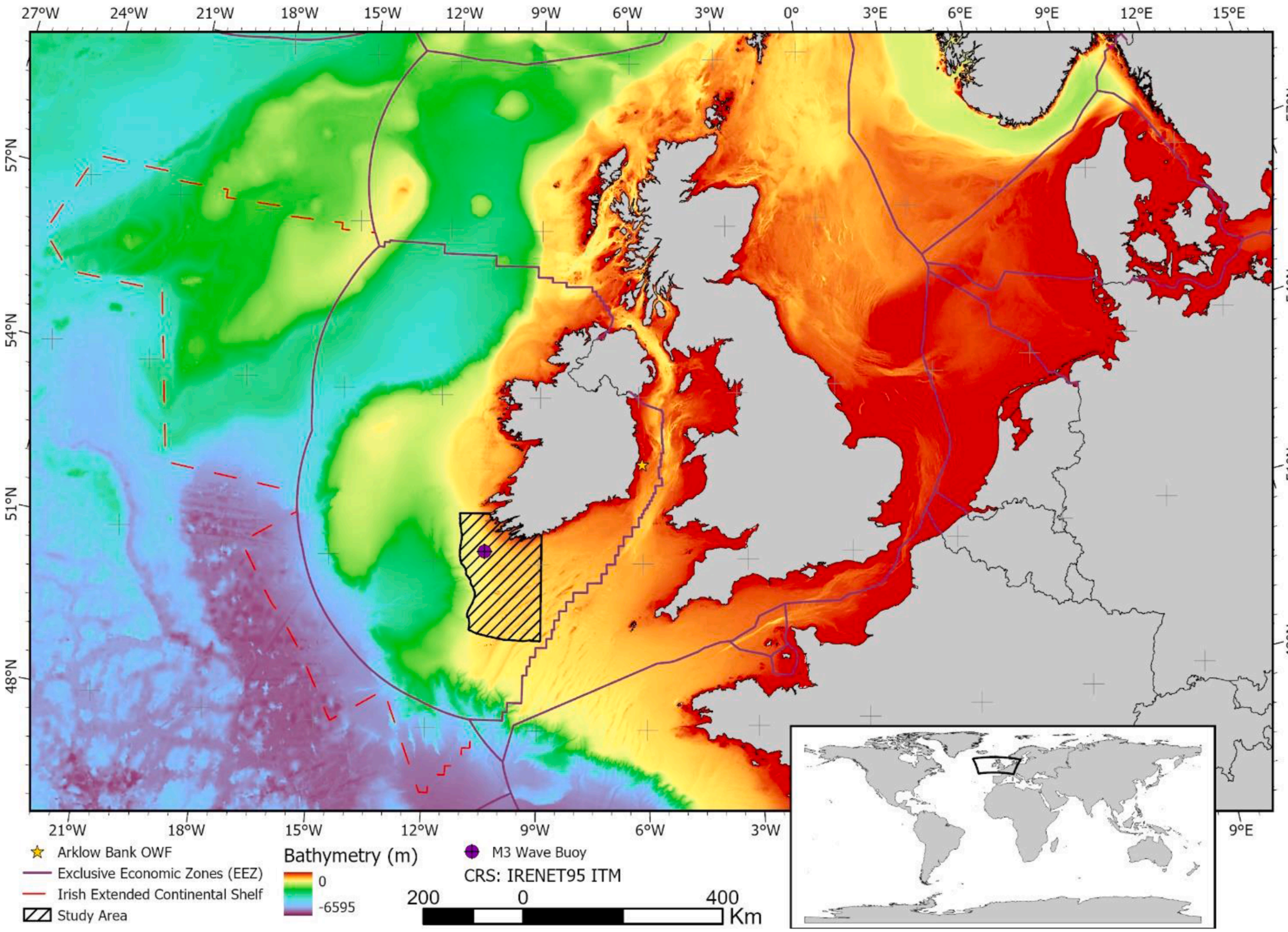

Fig. 1. Overview map of the northeast Atlantic shelf with GEBCO bathymetry (GEBCO Compilation Group, 2020) and national jurisdictions (Flanders Marine Institute, 2019) with the case study area in the southwest of Ireland.

sources by highlighting benefits, quantifying trends, and developing new mechanisms for investigation and cooperation.

The offshore wind energy (OWE) industry is growing as climate change curtailment initiatives and goals for reducing carbon emissions — often spurred on by underlying financial or public health and security priorities — drive the development of renewable energy (Scott et al., 2021). Europe has emerged as a leader in decarbonising electricity, where national goals are driven by concerns for climate change and energy security as well as opportunities for economic growth and employment (European Parliament, 2009). In 2019, OWE grew to account for 10% of the wind energy market (IEA, 2020b) and in Europe 3,623 MW of installed OWE capacity were added to electrical grids (Walsh, 2020), equal to 24% of the European wind energy. Similarly, most OWE research is conducted in Europe, with a considerable body of work dedicated to the site selection and geographic aspects of zoning offshore wind (Peters et al., 2020d).

Marine spatial planning (MSP), originally defined as a process to achieve ecological, social and economic objectives in the allocation of maritime space to various users and conservation initiatives (Ehler and Douvere, 2007), has gained traction over the last decade, especially through the implementation of the Maritime Spatial Planning Directive (European Parliament, 2014). OWE became a driver for the early development of marine spatial plans in Europe, for example in Belgium (Douvere et al., 2007) and Germany (Kannen, 2014), because of its economic importance and spatial footprint. The increasing demand for maritime space to facilitate 'blue growth' causes increased competition and trade-offs, whereby traditional maritime sectors such as fisheries face a diminishing role (Suárez de Vivero et al., 2008). Moreover, the increasing trends in turbine height and wind farm footprint have specific impacts on cultural ecosystem services. These cultural ecosystem services support important economic sectors such as tourism, as well as generating economic value for coastal properties with sea views (Robert, 2018; Gibbons, 2015). Despite, positive attitudes towards the shift to renewable sources of energy, social perception can often be negative toward the development of such infrastructure (Roche et al., 2016; Qazi et al., 2019; Segreto et al., 2020). Hübner et al. (2023) found that effects on residents and nature, economic impacts, social norms, attitudes about energy transitions and confidence in the planning process explained wind energy acceptance well through an integrated acceptance model. Greater public awareness about renewable energy has been recognised as an important factor important to its success (Qazi et al., 2019; Segreto et al., 2020). As society looks at the ocean for solutions to mitigate the climate crisis (Hoegh-Guldberg et al., 2019; Searles Jones, 2019), the renewable energy revolution challenges existing frameworks for resource allocation, questions fundamental societal values, and tests our existing planning structure and political decision-making processes.

In order to achieve lasting success, the OWE industry must avoid the pitfalls of 'ocean-grabbing' (Bennett et al., 2015). Instead of scrambling for seabed leases in yet another 'gold-rush' for natural resources, it is paramount that this industry strives to become a steward of the environment and a good neighbour to existing maritime stakeholders (sensu Bennett et al., 2019). Careful spatial planning is a key ingredient to the success of offshore renewables considering the inherently spatial consequences to development and required capital investment to achieve the renewable energy transition, which must be stemmed by a mixture of private equity and tax-payer support (Cummins et al., 2020). For Ireland alone, estimates project that €8.6bn of investment are required to achieve the country's 2030 climate action plan of developing 3.5 GW of offshore wind energy (The Carbon Trust, 2020). This study aims to improve pathways for optimising the societal, environmental, and economic costs of moving renewable energy generation offshore. To do so, this research draws on the theory of multiple-criteria decision making and proposes a novel combination of proven analytics to improve marine spatial planning tools. The effects of this approach are revealed using an OWE site selection case study off the southwest of Ireland.

Ireland is a relatively late mover in OWE, with only one offshore wind farm (OWF) to date: the 25MW Arklow Bank array commissioned in 2004 (Fig. 1). This raises potential concerns over the feasibility or motivation to tap into Ireland's offshore wind resource considering the relative abundance of similar windfarms in other European territories and the nearly two decades of inaction since Arklow's commissioning — also highlighting the importance of the research presented here. Despite the ongoing hiatus in new Irish offshore wind energy construction, the government has committed to producing 70% of its electrical needs with renewable energy sources by 2030, which will likely include a contribution of 12–35% from OWE (EirGrid, 2019). The extent to which offshore renewables will contribute towards Ireland's renewable energy targets will depend in part on planning constraints on land. Land-based wind generation is possible at lower levelised cost of energy (LCoE) and thus the first subsidy-free Spanish wind farms were already awarded in 2016 auctions (IEA, 2017). However, further onshore development has increasingly run into resistance because of competing land uses, noise pollution and visual impact. Increasing development area and turbine size are thus key benefits that motivate OWE installations despite the increased cost in capital, operational, and decommissioning expenditure. Jansen et al. (2020) projected that OWE in favourable sites of mature markets will break-even under market prices by 2023. Within the framework of technological innovation systems, Ireland is an example of a bottleneck to transitions where innovation, in this case OWE, is highly contextual to the local ground conditions, which has thwarted knowledge-mobility and spillover from the UK, Europe's largest OWE generator (sensu Binz and Truffer 2017).

While Ireland does not represent a mature market because it lacks expansive, shallow-water sites such as the Dogger Bank in the North Sea, the wind resource is very favourable. The wind regime of Ireland was found to be relatively strong through early modelling efforts (Petersen, 1993; Troen and Petersen, 1989). Using satellite data, Remmers et al. (2019) found that the high levels of wind energy density in the Irish Exclusive Economic Zone (EEZ) are inadequately described by classification systems that have been previously used for offshore waters off Brazil, the Iberian Peninsula, and the Mediterranean Sea (Balog et al., 2016; Pimenta et al., 2008; Salvação et al., 2015). The advent of floating OWE platforms opens a vast area of the Irish EEZ to potential windfarm development, especially off the west and south coasts. However, it is imperative to critically assess the difference between the overall theoretically accessible wind resource and the technically and socio-economically feasible development area (McKenna et al., 2020).

The role of experts in decision processes that enable the energy transitions has been highlighted in various studies (e.g. Daim et al., 2012; Antal 2019; Sorman et al., 2020). At the same time, the performance of experts in decision making and forecasting under uncertainty has been subject to long-standing debate (e.g. Armstrong 1980; Johnson 1988). Assessments to delineate the technically viable and socially acceptable area for renewable energy development on land thus include participatory mapping projects (e.g. Höltinger et al., 2020) and spatial sustainability assessments using a multi-criteria approach (e.g. Eichhorn et al., 2019) that also account for political acceptance amongst stakeholders. At sea, geospatial multi-criteria decision support tools have been developed to identify areas of high development potential (e.g. Cradden et al., 2016), quantify the number of competing interests (e.g. Jongbloed et al., 2014), and complete more comprehensive assessments that consider technical, economic, social, and environmental sustainability (Vagiona and Kamilakis, 2018). Multi-criteria decision analysis (MCDA) is the assessment of a set of solutions against a set of criteria that differentiate the solutions (e.g. Sharma et al., 2020). It is hence integral to any MCDA study that the weighting of criteria is given serious consideration. However, most geospatial multi-criteria decision aids are designed with user-modifiable weights (Cradden et al., 2016) or base the criteria weights on the authors' expertise (e.g. Vagiona and Kamilakis, 2018; Pınarbaşı et al., 2019). The present study advances these methodologies by devising a framework for weighing key physical, environmental, and technical criteria for offshore wind MCDAs through an innovative application of the Analytical Hierarchy Process (AHP) to synthesise the judgments of 25 experts from industry and academia (Peters et al., 2020c).

AHP is a mathematical decision aid (Saaty, 1980, 1987) often used to make quantifiable comparisons between choices based on otherwise disparate factors (e.g. Höfer et al., 2016; Wu et al., 2018). These calculations are used to rate the relative importance of a series of parameters commonly used to assess the suitability of proposed offshore wind energy development sites. The responses are then assessed to quantify variability and thus the differences in opinion within the pool of highly qualified survey participants. Internal inconsistencies in how important any one factor is within one respondent's answers are accounted for by adjusting pairwise comparisons using the method of Cao et al. (2008). Once adjusted, the AHP scores are rendered sufficiently valid (i.e. internally consistent) and compatible to be statistically described and to enable raster construction and geospatial comparisons of results.

Critically, the results of MCDA and AHP analyses are only as good as the expert opinion used to inform the analyses and, like all opinions they are inherently biased to some degree. The significance of different priorities in MCDA models when selecting amongst alternative energy sources has previously been highlighted in the transition literature (Shmelev and Van Den Bergh, 2016). This problem persists when searching for optimal locations of a single renewable energy source. Through the work presented here, the disparity amongst opinions from viable experts is illustrated as well as quantified geographically and the importance of bias reduction while conducting research or making policy decisions is highlighted. Expert judgement is indispensable when various input data for a decision process cannot be reduced to simple cost-benefit equations. However, with multi-disciplinary components to a non-linear algebraic expert judgement model (such as the AHP), expert disagreement is a likely result of judgemental unreliability (Mumpower and Stewart, 1996). There are limited resolutions for such disagreement such as fuzzy set decision-making frameworks (Liu et al., 2017; Abdel-Basset et al., 2018), and group evaluation methods based on correlations amongst experts (Abdul et al., 2022). Here, a stochastic method of harmonising a pool of expert responses while maintaining mathematical integrity is presented to minimise the inherent hazard of decision-maker bias. Finally, the results of the aggregated responses are used to develop a geospatial MCDA for an offshore wind energy site-selection case study that illustrates the more focused results of the new weighting method and multiple benefits to planning efforts. Together, these results have the potential to enhance the essential research and planning that will be required to transition society away from the current paradigm of 'traditional' fossil fuel dependence and thereby improving on a fundamental assessment problem and enhancing subsequent policies and development efforts. This potential is corroborated by new research that reveals the importance of such innovations in affecting responsible policy change in 'follower countries' within the European Union (Sawulski et al., 2019). The Irish OWE market has seen little progress over the past 19 years despite the stated intentions of the Irish government and the availability of abundant wind resources (Cummins et al., 2020). Thus, considerable improvements in how priorities are assessed and used to steer policies are needed to help Ireland meet its renewable energy goals and realise its potential to become a wind energy innovator. Importantly, these characteristics make Irish energy transitions a potential blueprint for other nations attempting to make similar innovations.

2. Methods

To arrive at a comprehensive GIS-MCDA, geographic and expert survey data were carefully treated in numerous steps outlined in Fig. 2 and sections 2.1–3.3. Section 2.1 introduces the attribute weighting using the AHP and Table 1 summarises the input data for the GIS-MCDA. Section 3 (Calculation) presents practical developments on processing AHP criteria weights for improved consistency in subsection 3.1, and details on geospatial data processing to obtain standardised inputs in subsection 3.2. Calculations to synthesise data are described in subsection 3.3 (Fig. 2).

2.1. Expert surveys

Surveys to obtain data for an AHP assessment were designed for compatibility with other assessments following well-established protocols and design axioms (Saaty, 1987; Saaty and Ozdemir, 2003; Ergu and Kou, 2012). A stakeholder workshop was convened and attended by offshore renewable energy developers and researchers supporting OWE with the goal of determining, in the Irish context, the key attributes that are required by an MCDA-tool to find optimal locations for OWE farms from available geo-spatial data (Table 1). To this end, nine attributes were selected for pairwise comparisons, the maximum number to elicit valid and statistically robust responses with limitations in human concentration and integrating disparate information (Saaty and Ozdemir, 2003). The nine variables were chosen from a pre-selection of 14 variables (Liu et al., 2017, Peters et al., 2019a, b), narrowed down during the workshop to minimise splitting bias, an artefact of criteria with more sub-attributes gaining weight in the decison process (Hämäläinen and Alaja,

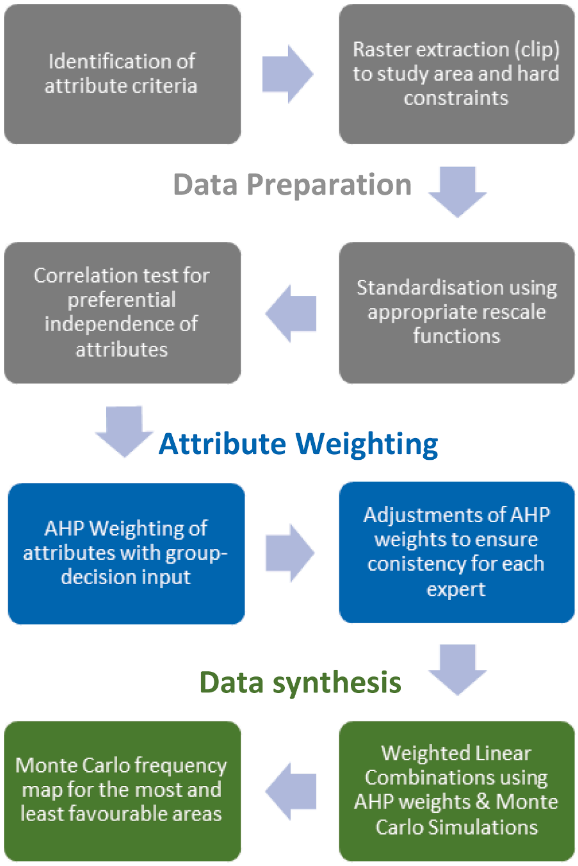

Fig. 2. Flowchart of GIS-MCDA and weighting methodology.

2008). In addition to the main goal of determining optimal OWE sites, within the context of this study, two additional objectives were posed namely: 1) to ensure the application of well-considered weighs to GIS model parameters, and 2) to assess the importance/appropriateness of the AHP for weighing model parameters.

Following the stakeholder workshop, survey questionnaires (see supplementary information file SI1) were completed over a five-week period from November 1st, 2019 by 6 wind energy industry specialists and 19 academic experts. Respondents were participants in a multidisciplinary research project to identify the potential and challenges for the Irish Offshore Renewable Energy transition and/or researchers in related fields. All researchers were members of a centre focused on the energy transition, climate action and the blue economy, comprising nine specialists in marine engineering, four governance & policy researchers, three marine ecologists, three geographers / remote sensing specialists, one geologist, one economist / business modeller and a climate scientist (participating scientists may have held expertise in more than one of these fields, see Peters et al., 2020c).

The survey was divided into two sections: an Individual Parameter Assessment (IPA) and pairwise comparison of model criteria. The IPA provided qualitative data on the relative importance of various criteria and allowed checking Pairwise Comparison Matrices (PCMs) and adjusting pairwise responses to improve consistency. The reciprocal nature of PCMs required a total of 36 comparisons to obtain a complete square matrix for the nine criteria assessed in this study.

3. Calculation

3.1. AHP data processing

In the IPA, survey participants were asked to score criteria on a scale from 1 (least important) to 17 (most important), with the midpoint (=9) signifying neither important nor unimportant. This system optimises comparability with the AHP matrix, which is assessed on a scale of 1/9 to 9 – a range with 17 increments (Saaty, 1987). Normalised weights were calculated from pairwise comparisons based on the principal eigenvector, and a Consistency Index (CI) was derived from the corresponding eigenvalue λ_{max} (Saaty, 1987). The Consistency Ratio (CR) is a metric defined as the consistency index divided by a random index RI_n (in this case RI_9=1.45), given in Eqs. (1) and (2).

$$CI = \frac{\lambda_{\max} - n}{n - 1} \tag{1}$$

$$CR = \frac{CI}{RI} \tag{2}$$

Where the CR was greater than 0.1, adjustments were made using an *a priori* framework. This was necessary in order to improve the consistency of results and thus the validity of priorities assigned to the criteria Saaty, 2003). Adjusted PCMs were calculated following the method of Cao et al. (2008), using an adjustment parameter γ_a=0.98. Whenever this adjustment caused inacceptable deviations from the original survey matrix, i.e. when $\delta > 2 \vee \sigma > 1$ (Eqs. (3) and ((4), see Xu and Wei, 1999), a single adjustment to an AHP score was made, based on which pairwise comparison had the greatest effect on the maximum eigenvalue (Saaty, 2003).

$$\delta = \max_{i,j}\{|b_{i,j} - a_{i,j}|\} \tag{3}$$

$$\sigma = \frac{\sqrt{\sum_{j=1}^{n}\sum_{i=1}^{n}(b_{i,j} - a_{i,j})^2}}{n} \tag{4}$$

Where $B = \begin{pmatrix} b_{1,1} & \dots & b_{1,n} \\ \vdots & \ddots & \vdots \\ b_{n,1} & \dots & b_{n,n} \end{pmatrix}$ is the adjusted matrix of $A = \begin{pmatrix} a_{1,1} & \dots & a_{1,n} \\ \vdots & \ddots & \vdots \\ a_{n,1} & \dots & a_{n,n} \end{pmatrix}$

For eleven surveys, where $\delta > 2$, a single adjustment to the PCM was made by determining the highest value $\varepsilon_{i,j}$ (see Eq. (5)), and replacing the corresponding value $a_{i,j}$ with a more consistent score as described by Saaty (2003). Following this adjustment, the algorithm by Cao et al. (2008) was run and rendered sufficiently consistent results with for eight respondents based on the thresholds defined by Xu and Wei (1999). Three surveys, two from researchers and one from an industry participant, still failed to meet this criterion (of $\delta < 2$). Thus, 22 surveys were used to calculate mean criteria weights, and a similar ratio of $\sim 1/3$ between industry and research survey participants was maintained. All calculations were implemented using *numpy* routines in Python 3.7.

$$\varepsilon = A \circ W, \tag{5}$$

where

$$W = \begin{pmatrix} \frac{w_1}{w_1} & \dots & \frac{w_1}{w_j} \\ \vdots & \ddots & \vdots \\ \frac{w_i}{w_1} & \dots & \frac{w_j}{w_i} \end{pmatrix}$$

Comparisons to IPA scores and original AHP weights were drawn to ensure that the adjusted results did not deviate substantially from the original judgement provided by the survey participants. Both adjusted and raw weights are presented as part of the results (section 4.1) and adjustments merely served to improve the PCM consistency, increase the number of viable responses, and thus build confidence in the data.

3.2. Geospatial data processing

A geospatial MCDA for SW Ireland was performed to demonstrate the utility of the AHP adjustments for deriving parameter weights and enable quantifiable comparisons between differently weighted versions of the same MCDA. Geospatial raster data layers for the selection criteria listed in Table 1 were collated and transformed to a uniform 1 km horizontal resolution and an evaluation scale of 1–100 to allow comparisons. The following sub-sections detail the original data sources and all relevant processing steps to arrive at the final data layers for the geospatial MCA.

3.2.1. Wind

Five-year half-hourly instantaneous time series of wind speed at 100 m a.s.l. and a reference height of 10 m a.s.l were downloaded from the New European Wind Atlas,[2] with a horizontal resolution of 3 km. The data at 10 m a.s.l were validated against the Met-Éireann M3 buoy in the study area, indicating a very strong correlation (Pearson R correlation coefficient of 0.89). Capacity factors based on available power data for the most modern wind turbines (Fig. 3A) were derived for each half-hourly data point across the study area and the five-year time series using routines in the R programming environment (R Core Team, 2022), allowing the average percentage of MW-output relative to a turbine's rated power over the five-year period to be computed. The resulting layer ranged from 43.9% to 57.3% in the study area and values were stretched linearly to the evaluation scale.

[2] Data obtained from the New European Wind Atlas, a free, web-based application developed, owned and operated by the NEWA Consortium. For additional information see www.neweuropeanwindatlas.eu.

Table 1
Selection criteria for the AHP-weighted multi-criteria decision analysis with their respective data source, resolution and geoprocessing operations performed during analysis, for details see Section 3.

Criteria	Description	Source	Original Resolution	Resampling to 1 km grid	Transformation Function
Wind Speed	Wind-speed derived capacity factor for 5 years of modelled data at 100 m a.s.l.	New European Wind Atlas	3 km horizontal and hourly temporal	Cubic convolution	Conversion to capacity factors based on available turbine power data followed by a linear stretch
Water Depth	Bathymetric data mostly based on high-resolution multibeam echo sounder surveys	EMODnet	93 m horizontal resolution	Cell-averaging	$m(x) = 104 - 4/5x,\ x < 40,$ $j(x) = 214 - 71/20x,\ 60 > x \geq 40,$ $f(x) = \frac{6.265}{10^5}x^3 - \frac{3.13}{10^2}x^2 + 5x - 200,$ $60 \leq x \leq 200$, where x denotes depth
Wave Height	Percentage time of wave height below 2.5 m threshold based on WaveTechIII models over three years	CMS NWS WaveTechIII	0.017° spatially and one-hour temporally	Cubic Convolution	ESRI Large function with a midpoint = 50, spread = 3 and upper threshold = 80, above which all cells obtain maximum values
Ocean Current	Surface current daily maxima averaged over a three-year period	CMS NEMO	0.017° spatially and one-hour temporally	Cubic Convolution	ESRI Small rescale function with a default midpoint and spread of three. Inverted to account for the negative effect of currents
Seabed mobility	Index of likely seabed mobility based on surface sediment from sediment grab data and bathymetry derivatives	Peters et al. (2020)	500 m x 500 m	Cell-Averaging	Linear Stretch
Depth to Bedrock	Depth of bedrock below seafloor estimated based on available data on rock outcrops and broad scale seismics	EMODnet & this project	1 km	NA	Logarithmic transformation with lower and upper thresholds at 50 and 2000, beyond which all cells assumed 1 &100 respectively
Infra -structure	Incorporates information on offshore distances to appropriate ports and potential grid connections	This project	1 km	NA	ESRI Small function with a default midpoint and a spread of 5
Biological Factors	Fish & marine mammal distribution and seabird vulnerability data	Critchley & Jessop (2019), Gerritsen & Kelly (2019b)	5 km 1 km	Cubic Convolution N/A	Birds: ESRI Small function with the first quantile as a midpoint and a spread of 1. Fish: identical, except default midpoint
Visibility	A viewshed analysis of turbine visibility from coastal areas	This project	1 km	N/A	Trigonometric ratio (see 3.2.9) and linear stretch

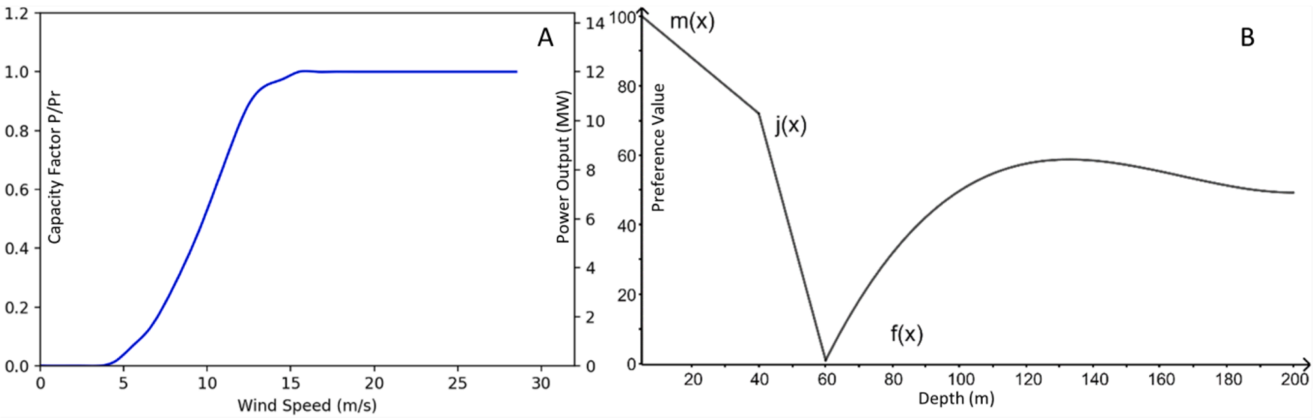

Fig. 3. (A) Best available power data to convert wind speed to capacity factors based on a Vestas V164–8.0 MW, an Aerodyn 8MW and an Enercon 7.5MW floating wind energy platforms and (B) relative preference for depths using monopile foundations (m(x)), jacket foundations (j(x)) and floating substructures (f(x)).

3.2.2. Water depth

Bathymetric data were obtained from EMODnet (EMODnet Bathymetry Consortium, 2018), providing coverage of the study area at a horizontal resolution of 93 m. The data were resampled to 1-km grid size using cell averaging. The ideal depth for offshore wind is mainly a function of the substructure technology. Myhr et al. (2014) discussed the effects of depth on LCoE, however, technological advances have driven prices down over the last few years. Findings of the EirWind project (https://www.marei.ie/project/eirwind/) indicate that jacket foundations may now outcompete monopile foundations from a depth of about 40 m. The rate of change in cost of fixed foundations probably still increases with the transition to jacket foundations, becoming inviable for economic reasons at depths greater than 50 m (Myhr et al., 2014), reflected in the transformation to preference values on the 1–100 evaluation scale (Fig. 3B, Table 1). Numerous prototypes of floating foundations have been developed to develop OWFs at greater depths and installation and maintenance cost is less sensitive to depth but full commercial implementation is yet to be achieved (Campanile et al., 2018; Myhr et al., 2014). Therefore, preference values for depths accessible using floating substructures increase steeply from 60 m, the transitional depth between fixed and floating technologies, and remains relatively level at greater depths. Owing to the greater cost of installation and thus LCoE as well as uncertainty over the timing of when the technology becomes ready for deployment, preference values for depths accessible through floating substructures remain below the ones for monopile and shallow jacket foundations (Fig. 3B).

3.2.3. Significant wave height (H_s)

A three-year time series of hourly instantaneous H_s based on the WaveTechIII model, reanalysed by the UK Meteorological Office for the Northwest European shelf, was obtained from the Copernicus Marine Service (CMS). The data were validated against the M3 weather buoy data following the methodology of O'Connell et al. (2020), who assessed an earlier version of this model at a coarser spatial resolution. Bias was found to be <12 cm, though the model tended to underestimate wave height. A Pearson correlation coefficient of $R = 0.95$ indicated a very good fit. The preference for areas based on significant wave height was calculated based on a modified methodology of the UK Crown Estate (The Crown Estate, 2019), which describes areas with an $H_s > 2.5$ m more than 80% of time as unviable to offshore wind development because of restrictions to installation, maintenance, and decommissioning weather windows. Considering efforts to improve technology for conducting offshore operations in less amenable conditions and trends in potential deployment conditions (e.g. Sun et al., 2012; Peters et al., 2020d), the percentage time of $H_s < 2.5$ m was computed in R as an opportunity model. Results ranged from 37.2 to 100% and were transformed to the model evaluation scale using the ESRI 'Large' transformation function giving preference to higher values.

3.2.4. Ocean currents

Hourly-instantaneous surface currents based on NEMO (Nucleus for European Modelling of the Ocean) model data from 2017 to 2019 were downloaded from the CMS database. This model assimilates tidal data at 1.5 km resolution and the final product is provided at a 0.017° cell size. Daily-maxima were identified and averaged across the three-year time series using raster routines in R. The resulting layer was resampled to a resolution of 1 km using cubic interpolation and transformed to the evaluation scale using the ESRI 'Small' function, thereby assigning higher and thus preferable values to areas with lower currents.

3.2.5. Seabed properties

The Irish seabed is highly heterogeneous due to the impact of various Quaternary glacial, periglacial, and postglacial processes (Peters et al., 2020a, 2015; Tóth et al., 2020; Van Landeghem et al., 2009) and diverse metocean conditions around the island of Ireland. The seabed stability data from Peters et al. (2020b), describing seabed properties through an opportunity model for offshore wind developments, was used for this model. The original data were supplied by INFOMAR, EMODnet, and UCC (EirWind) research cruises. The model output was resampled from 500 m to 1 km resolution and clipped to the study area in the south-west of Ireland. The resulting layer with a range from 100 to 325 on a unitless index was rescaled linearly to the evaluation scale of 1–100.

3.2.6. Depth to bedrock

Depth to bedrock was modelled using known rock outcrops from EMODnet substrate data. The substrate data was rasterized and a proximity raster from rock substrate was created at a resolution of 1 km. Bedrock depth was approximated by assuming a linear increase from known rock substrates at a slope angle of 5° Bedrock depth was then capped using crystalline basement depth from Straume et al. (2019), which is based on seismic refraction data for the NE Atlantic region (Funck et al., 2017). The data were then transformed to the MCDA evaluation scale using ESRI's logarithmic rescale function to account for the wide range of values.

3.2.7. Distance to infrastructure

Distance to infrastructure is a surrogate criterion that accounts for the proximity of any given site to appropriate port as well as potential grid connections, which would have been non-redundant and inflated the number of criteria if considered separately. Shannon and Cork ports were used as relevant ports for the study area, and grid connections were derived from the existing EirGrid network and planned interconnectors through the Celtic Sea. A separate raster layer for 'distance to ports' and 'distance to grid' was computed using the ESRI cost-distance tool in ArcPro at 1 km resolution and combined at a ratio of 1:2, accounting for the higher cost of export cables compared to transportation of crew and resources between ports and an offshore windfarm site. The resulting raster was rescaled to the evaluation scale using the ESRI 'Small' function, which accounts for non-linear distance decay approximating an inverse exponential relationship at great distances (Malczewski, 2000), as well as mobilization costs that affect short journeys proportionately more.

3.2.8. Biological features

The biological constraints model is composed of a seabird vulnerability model (Critchley and Jessop, 2019a) and commercial fishing data (Gerritsen and Kelly, 2019a). Migratory seabirds are the animals exposed to the greatest direct risk from wind turbines, due to direct collisions as well as their vulnerability to displacement (Critchley and Jessop, 2019b). Critchley and Jessop (2019) modelled the vulnerability collision and displacement for seabirds based on data from Rogan et al. (2018) at a national scale covering the Irish EEZ for winter and summer. The displacement vulnerability index and collision vulnerability index accounting above 40 m were averaged across seasons for the study area. The data were rescaled to the evaluation scale of 1–100 using the ESRI 'Small' function with a midpoint set to the first quantile and a spread of 1, in order to achieve gradual increase to values of high preference with increasing distance from the bird colonies that cause high collision and displacement vulnerability in the northwest of the study area.

The effect of OWFs on fish is subject to academic debate (Hunt and Jessopp, 2019). While the exclusion of fisheries creates conflicts with fisheries, it may also have a net positive effect on fish stocks at least on a localised scale. However, there is no evidence of significant spill-over effects at a regional scale. Stakeholder consultation processes and fishery compensation payments for the loss of income are costs to the industry. In addressing this problem and predicting costs, data deficiency is problematic, especially for small-scale fishing vessels <12 m length, that typically fish within the territorial waters. Therefore, good stakeholder engagement processes are key to successfully designate offshore wind development zones as well as develop any windfarms therein. However, the extensive VMS fishing data that have become available through recent work of Ireland's Marine Institute (Gerritsen and Kelly, 2019b, 2019a), provides useful input for opportunity-constraint modelling and an MCDA. The fishing value of 8 gear types used by Irish vessels between 2014 and 2018 was summed using raster cell statistics in ESRI ArcGIS Pro and transformed to the MCDA evaluation scale using ESRI's 'Small' transformation function to treat areas with low fishing value preferentially.

The resulting rasters for fishing effort and seabird vulnerability were averaged to produce a composite biological layer, which was stretched to the evaluation scale. Thus, high values (approaching 100) indicate that areas are more favourable for offshore windfarms due to lower abundance of fish and vulnerable seabirds.

3.2.9. Visual impact

The next generation of offshore wind turbines will reach heights of 260 m, with a hub height of 140 m and rotor diameter of 220 m. While their increased size and improvements in technology implies that fewer turbines are required per gigawatt of electricity, every single turbine will be more visible at greater distances. Thus, an offshore windfarm visibility assessment was produced using residential and tourism information.

In order to estimate the visual effects on residents, Central Statistics office (CSO) population density data from the 2016 census were used to create a weighted population model for coastal communities within 10 km of the southwestern shorelines of Ireland (CSO, 2019). A power transformation was employed to rescale the population density values of the CSO small area to a 'population weighting' scale of 1–100. The data were transformed in the shapefile attribute table using the exponential scale function native to

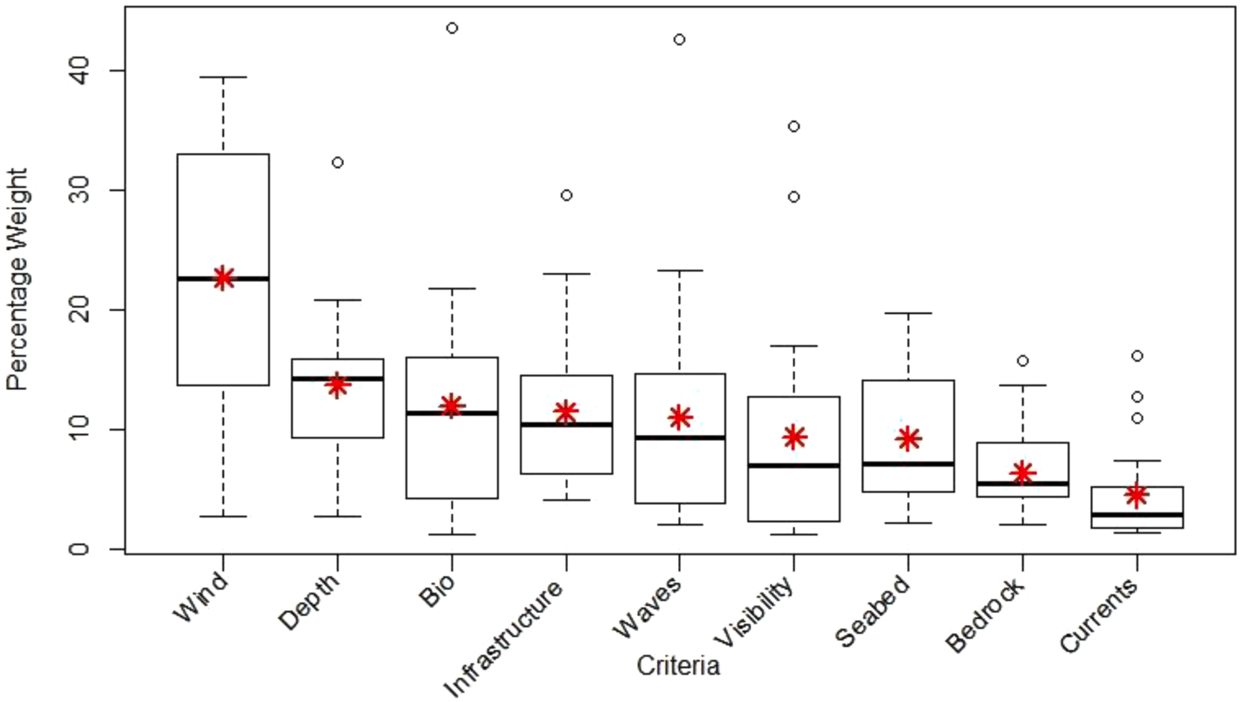

Fig. 4. Box and Whisker plot of AHP-derived criteria weights based on 22 respondents and algorithmic adjustments to improve consistency (Cao et al., 2008; Saaty, 2003). Red * indicates mean values; dots mark outlier responses from individual surveys beyond 1.5*IQR.

QGIS and an exponent of 0.3. Under this transformation values increase relatively quickly initially and then flatten out toward higher population densities, thereby avoiding a reduction of all sparsely populated areas to values near 1 and accounting for the scenic value of rural areas. The 25 m Irish DEM within 10 km of the shoreline of the study area was resampled to 100 m horizontal resolution and used to calculate slope aspects. This raster was then vectorised to points, and all points with a slope aspect that points approximately toward the coastline were selected (within a 60° angle inshore of the direction of the coastline, generally using 70° and 270–330° as minimum and maximum azimuths respectively). A spatial join was created between the points and the CSO small population areas, and the 'population weighting' scale was used to randomly select points with a custom-built tool in QGIS based on the 'random selection within subsets' processing tool. Using this method, ~400,000 observer points were selected, and a viewing angle of 120° (aspect ±60°) was applied. The points were then used with an observer's height of 1.6 m and a target height of 260 m to create a cumulative binary viewshed using the visibility analysis plug- in QGIS (Čučković, 2016) on the 100 m DEM and extending to a maximum distance of 65 km.

In order to approximate the effects of turbine visibility on the travel and recreation sector, a tourism viewshed index was derived from important tourist attractions. As the most iconic route for tourists visiting the west coast of Ireland, the Wild Atlantic Way was used to estimate tourist flows. All vertices of the Wild Atlantic Way in the study area were turned into points using the 'extract vertices' tool in QGIS and a viewing angle of 120° was calculated. The direction of a vertex is the mean of the direction of the lines leading to and from the vertex. To create the viewing angle, 60° and 180° were subtracted from the vertex direction for the maximum and minimum azimuth respectively, as the Wild Atlantic Way runs approximately parallel to the shore. A cumulative viewshed was computed in QGIS, using an observer height of 1.6 m, target height of 260 m and a maximum analysis radius of 75 km to account for the numerous elevated viewpoints along the Wild Atlantic Way.

Both residential and tourism viewshed rasters were adjusted for distance to shore using trigonometric equations. Up to 5 km from shore, the visual impact was considered maximal. Beyond 5 km, a factor was calculated as the ratio of the perceived viewing angle of a turbine at any distance >5 km relative to the perceived viewing angle of a turbine at the 5 km reference distance (Eq. 6).

$$f(\theta) = \frac{\arctan\left(\frac{260}{D}\right)}{\arctan\left(\frac{26}{500}\right)},$$

where D is distance from shore and 260 m equals turbine height.

The touristic observer points are fewer in number, however the value of scenic views to tourism in West Cork and Co. Kerry is substantial and concentrated around the sites of the Wild Atlantic Way. The tourism viewshed and residential viewshed rasters were therefore given equal weight once the residential raster was normalised to the maximum value in the tourism raster. The resulting raster was rescaled linearly to the MCDA evaluation scale and inverted.

3.3. Multi-criteria decision analysis (MCDA)

The MCDA was implemented using the weighted linear combination method in python, after all pre-requisites for analysis were confirmed based on best practices outlined by Malczewski (2000). The redundancy of input layers was checked using pairwise Pearson product-moment correlation coefficients (Geneletti, 2007). Five of the 36 pairwise tests indicated positive relationships, mainly an artefact of the layers' partial dependence on distance from land. Examples include turbine visibility and bird collision risk, which both decrease with distance from the shore, where cliffs form important nesting sites as well as touristic viewpoints, or wave height increasing offshore along with distance to infrastructure connections. Distance to ports and distance to grid connections, which would have been nearly perfectly correlated were replaced with a combined surrogate raster for infrastructure in general to avoid erroneously inflating the importance of those layers (see section 3.2.7) and to help facilitate robust pairwise comparisons. While some correlations exist between the remaining layers, they are non-redundant in the sense that they account for vastly different criteria that uniquely affect the selection of development zones.

MCDA model runs were computed using AHP-derived weights of five individual respondents as well as aggregate weights to show the variation through expert opinion and bias and infer the effects of disparate opinion and criteria on spatial planning and decision-making processes. Comparable results were obtained using the technique for order of preference by similarity to ideal solution (TOPSIS). This generated a favourability score, equal to relative closeness C_i^* which was calculated on the Manhattan distance of every potential site (i.e. raster cell i) to the most ($= D_i^*$) and least-favourable ($= D_i^-$) areas:

Table 2
Adjusted AHP mean % weight, standard error of the mean (SE), coefficient of variation (CV) for all nine criteria in order of importance, and change in criteria rank based on AHP mean weights relative to IPA ranks.

	Wind Speed	Water Depth	Biological Constraints	Infra-structure	Wave Height	Visual impact	Seabed Stability	Bedrock Depth	Ocean currents
Weight $\bar{x}$	22.6%	13.7%	11.9%	11.4%	11.0%	9.3%	9.2%	6.4%	4.5%
SE	2.2	1.28	1.88	1.25	1.96	1.81	1.14	0.70	0.81
CV	0.49	0.47	0.79	0.55	0.85	0.97	0.62	0.55	0.9
AHP Rank vs IPA	0	0	+3	0	−2	−1	+1	−1	0

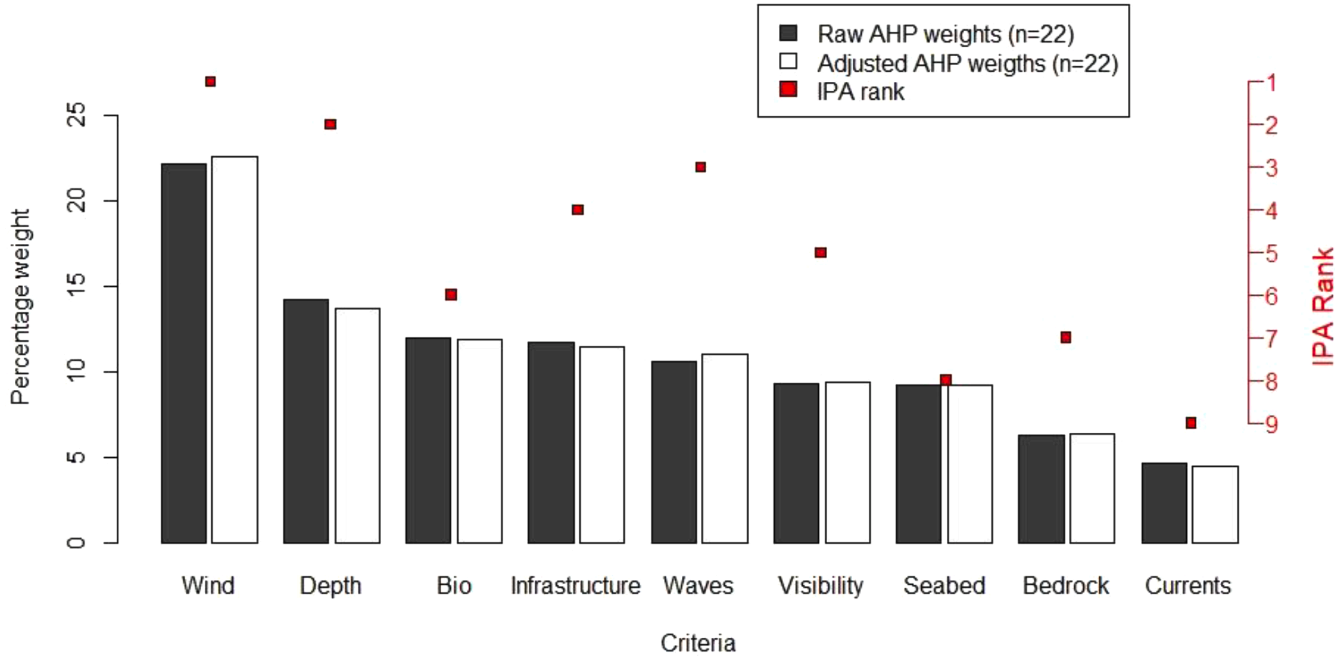

Fig. 5. AHP-derived weights with and without corrections following Cao et al. (2008) and Saaty (2003) and IPA ranks for all criteria on the secondary axis.

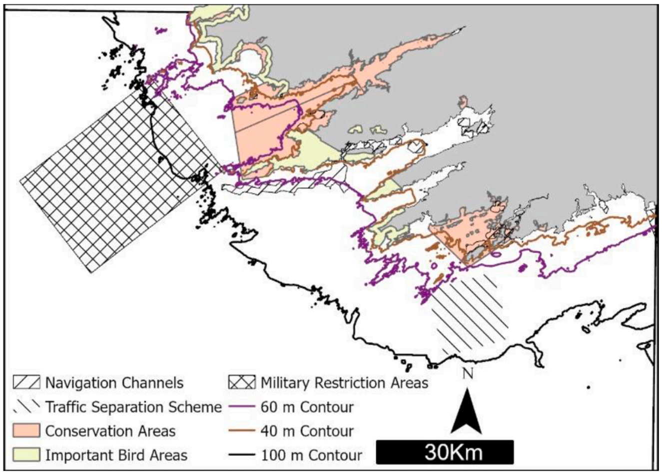

Fig. 6. Existing designations in the study area are concentrated near the coast. Navigation channels were derived using EMODnet AIS data for fishing, passenger, cargo and tanker vessels with a combined minimum of 3 shipping hours per month and km^2.

Table 3
Conflicting designations in% of the fixed vs. floating depth range within the study area.

	ng Designation Areas		
	% fixed		% floating
Navigation Channels	9.88%		0.13%
Traffic Separation Scheme	0.08%		1.77%
Military Restriction Areas	0.64%		2.91%
Conservation Areas	26.83%		0.42%
Total	37.43%		5.22%
	Shoreline Length in Important Bird Areas		
IBAs	16.40%		NA
	Relative size to total study area		
Area within fixed depths (≤60 m)		3.7%	
Area within floating depths		96.3%	

$$C_i^* = \frac{D_i^-}{D_i^* + D_i^-}$$

Finally, Monte Carlo simulations were computed using 1,000 sets of random-normal generated weights which fulfil four conditions:

- Each weight w_i is derived to two decimal points from a normal distribution $w_i \sim N(\bar{x}_i,\ \sigma) w_i \sim N(\bar{x}_i,\ \sigma_i)$, where $\bar{x}_i$ is the arithmetic mean and σ_i is the standard error of the 22 viable AHP responses for each of criterion i
- Each criterion weight is non-negative
- The sum of each set of random weights equates to one (1)
- All sets of weights are unique

A frequency map of the 10% most and least favourable areas was created to summarise the 1,000 resulting MCDA runs into meaningful and interpretable results.

4. Results

4.1. AHP-derived criteria priorities

The AHP-derived mean weights for the nine criteria selected (Table 1; SI2) affecting offshore wind farm site selection range from 4.5% to 22.6%, with considerable variation in the weighting of each criterion amongst respondents (Fig. 4). Most of the outliers were produced by researchers and may reflect inherent bias from expertise in a related field such as ecologists or oceanographers prioritizing biology or waves respectively. A notable outlier from an industry expert attributed the highest priority (~35%) to turbine visibility (Fig. 4, SI1).

Despite the large interquartile range of weights attributed to wind, the most important criterion based on mean and median weight (Fig. 4), the coefficient of variation (CV) in responses calculated as standard deviation relative to the mean weight was the second

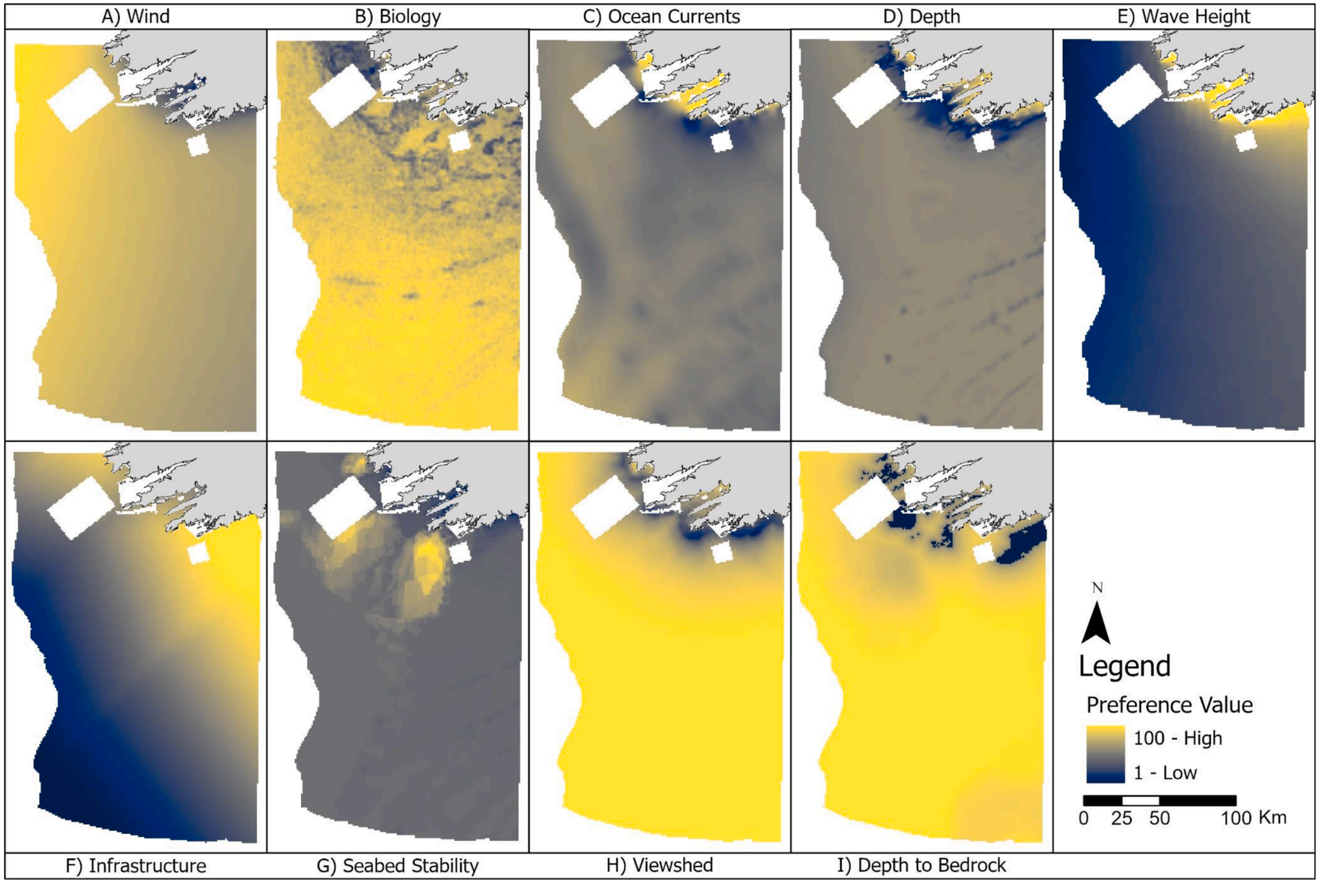

Fig. 7. The nine MCDA criteria transformed to the 1–100 evaluation scale following methods outlined in subsection 3.2 and Table 1 with layer symbology set to 'min-max stretch' in ESRI ArcGIS Pro.

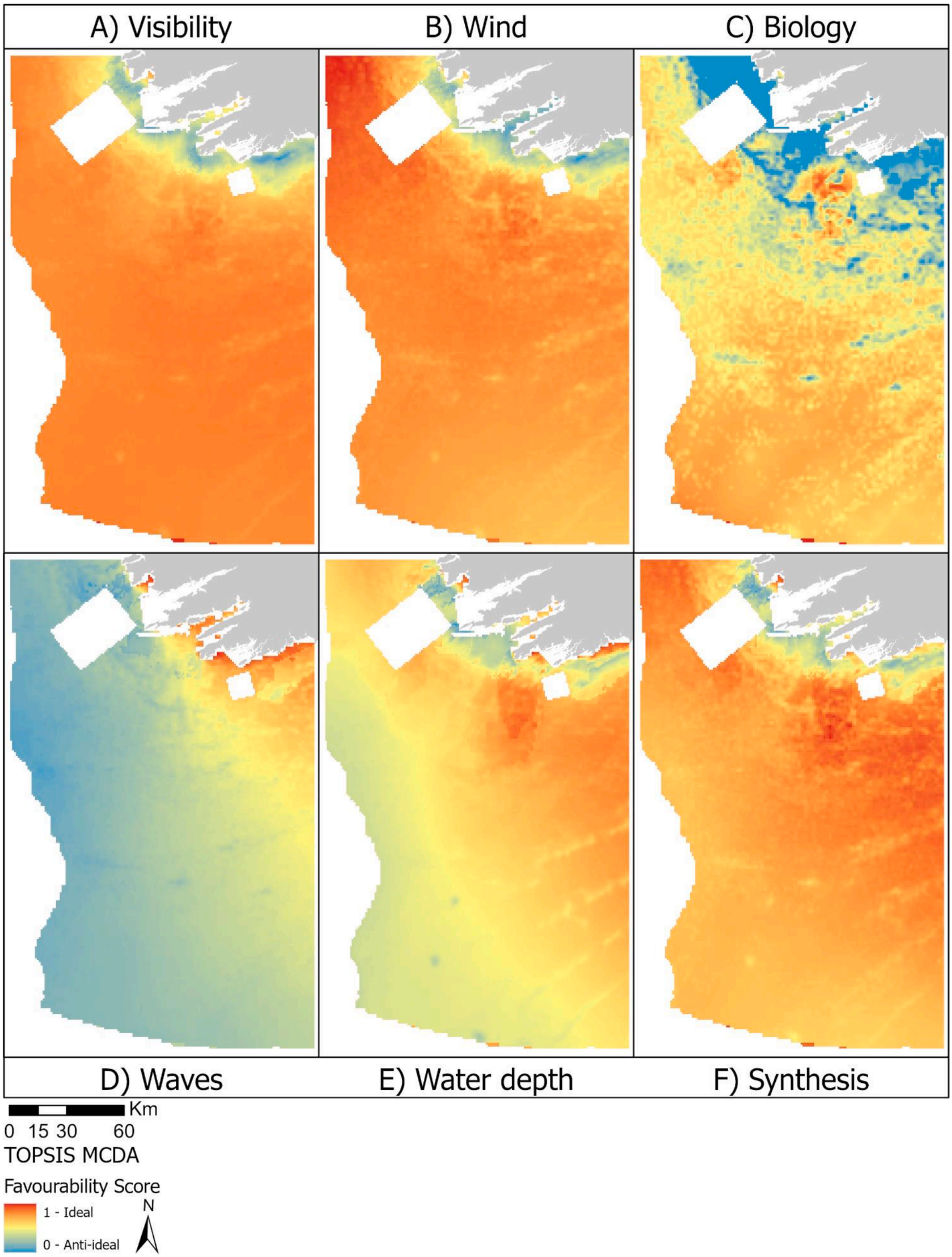

Fig. 8. Model simulations based on individual expert judgments. Industry experts (A) prioritised turbine visibility and (B) considered wind the most important criteria. Academic experts (C-E) were primarily concerned with biological factors, wave conditions and water depth respectively. Panels (A-E) highlight the effects of outliers in expert judgement (whereby the important single criteria accounted for ≥30%) and the potential implications of basing MCDA on only one expert's opinion. As such, this is not a representative sample of all questionnaires. (F) shows the results of a synthesis MCDA based on the mean of all 22 viable surveys.

lowest (Table 2) and close to the lowest CV of water depth. The importance of visual impact, ocean currents, wave height and biological constraints were subject to higher variation amongst survey respondents (Table 2).

Both raw and corrected AHP mean values are presented along with their respective IPA ranks in Fig. 5. The number of viable responses with a CR <0.10 increased from 7 to 22 following the algorithmic revisions of pairwise comparison matrices. The resulting change in criteria weight comparing the mean of the 22 viable adjusted and unmodified survey responses ranges from 0.01% (biological factors) to 0.54% (water depth) and is <0.45% for all other criteria (Fig. 5).

While the AHP adjustments ensured consistency and enabled the compilation of results into an average, this process had little effect on the overall ranking of criteria importance (Fig. 5). The ranking of four of the variables did not change when deriving weights from pairwise assessments compared to the initial IPA scores (Table 2). However, the importance of some parameters was judged much differently as an intuitive, individual assessment (IPA scores), compared to the more mathematically rigorous AHP appraisals. Most notably, biological constraints moved up three ranks at the expense of wave height and visual impact, however, the weight of these criteria are all within 2.6%. Wave height, which lost two ranks compared to its IPA rank had relatively good agreement in the AHP assessment (Fig. 5; Table 2).

4.2. GIS layers

Pre-existing designations including special areas of conservation, traffic separation schemes, military danger areas as well as approaches to ports heavily trafficked based on AIS data were excluded from the raster analysis and are presented in Fig. 6. The concentration of these designations in the near-shore environment, where the seabed is shallower, dramatically reduces the available space for fixed-foundation wind farms. Table 3 highlights this disproportionate concentration of activity near the shore, with >37% of the theoretical area accessible using fixed foundations being already designated in some other way, compared to 5% of the much larger area that could be developed using floating substructures.

The geographical raster data rescaled to the MCDA evaluation scale are presented in Fig. 7. Values for wind are lower closer to land, especially in coastal bays due to shielding effects, and increases towards the west. The large uninterrupted fetch of the Atlantic Ocean leads to relatively little variation in offshore wind data. Biological constraints are largest near bird colonies in the southwest of Ireland, as well as in regularly fished waters within 60 km from shore (Fig. 7B). These constraints decrease offshore, and thus biological suitability values are highest in the far south of the study area. Ocean currents are lowest in the bays of southwest Ireland and highest off the coastal headlands (Fig. 7C). Intermediate, wind driven currents appear to be ubiquitous in the rest of the study area with slight increases in areas of bathymetric highs. Fig. 7D illustrates the steeply sloping seabed in the nearshore environment of SW Ireland, with fixed depth evaluation values quickly decreasing with increasing distance from the coastline. Because of the transformation function for floating foundations, which are less sensitive to increasing depth, as well as the bathymetry of the Celtic shelf, the depth preference values remain relatively constant at depths of 75–200 m (Fig. 7D). Preference values based on wave climatology are high near the coast and especially inside bays, were landmass shelter the waters from swell and storms, thus providing longer weather windows for installation and maintenance. The available time of significant wave height below 2.5 m and thus the feasibility of installation and maintenance decreases offshore, shown by low values in Fig. 7E. Values for distance to infrastructure are least favourable in the southwestern extent of the study area (Fig. 7F). Influenced by ports and grid connections on the Irish west coast as well as in the south of Ireland, increasing values for the infrastructure criteria are evident both towards the north as well as towards the east of the study area. The highest values for sediment stability are found in the central northern region of the study area (Peters et al., 2020b; Fig. 7G). The visibility of turbines decreases from shore, with turbines likely to be completely invisible 65–75 km from shore due to the earth's curvature. Beyond this distance, suitability based on viewshed computations is highest. Due to the shielding of views by the rugged coastline, the increase in viewshed suitability is not linear and exhibits pockets of increased preference (Fig. 7H), though this computational approach fails to account for horizontal visibility as a result of bad weather and only assess a fair-weather scenario. Depth to bedrock is lowest in north-eastern patches of the study area (Fig. 7I), where European habitat maps indicate rock substrate. Closer assessment of bedrock depth and subsurface properties by means of seismic surveys, core and borehole investigations is critical in areas of interest to the offshore renewable industry.

4.3.1. Effects of individual and group decision making on geospatial MCDA results

A comparison of some of the individual experts' judgement to the mean of AHP-derived weights at this regional scale lays bare the significant effects disparate priorities have on the geospatial MCDA (Fig. 8). The priority attributed to turbine visibility by an expert for instance would lead all developments to be pushed further offshore (Fig. 8A), where the distance to ports and grid connections could dramatically increase the cost of installation, maintenance, and delivering power to market. Exaggerated weighting of the wind criterion distributes development viability predictions of the MCDA because wind is relatively homogenous in the study area (Fig. 6A and 8B). Conversely, the strong emphasis on a constraint criterion such as biological factors mostly serves to exclude small portions of the ocean from OWF development because they exhibit steep gradients from areas that are suitable to ones that are not (Fig. 8C). A focus on waves or water depth (Fig. 8D-E) places potential wind farm sites very close to shore, potentially disregarding technological and engineering solutions to deeper depths and less favourable wave climatology. Synthesising the preferences by all decision makers by aggregating the weights to mean scores provides a more balanced view of where offshore windfarms are most likely to be developed within the study area (Fig. 8F).

4.3.2. Monte Carlo simulation results

Given the level of variability of preferences expressed by this large group of experts, a stochastic approach is required to identify the likely best areas for wind farm developments. These results provide a clearer picture, indicating consistently low preference values for the nearshore areas and highest selection frequency of favourable areas in the east of the study area at 30–80 km from shore (Fig. 9). The observed patterns are similar to the ones observed from the synthesis MCDA, but the iterative approach using 1,000 Monte Carlo simulations adds confidence and the selection frequency map (Fig. 9) removes noise. The Monte Carlo MCDA helps account for the diversity in priorities expressed by experts completing the AHP survey, and filters trends in the data that stand based on a wide array of weights plausible based on the survey. The computation of preference areas does not require a minimum size to accommodate a wind farm and avoid patchiness. However, the continuous nature of the data with gradual changes from high to low preference areas for most constituent data layers produces coherent results that provide focus for potential offshore wind development zones.

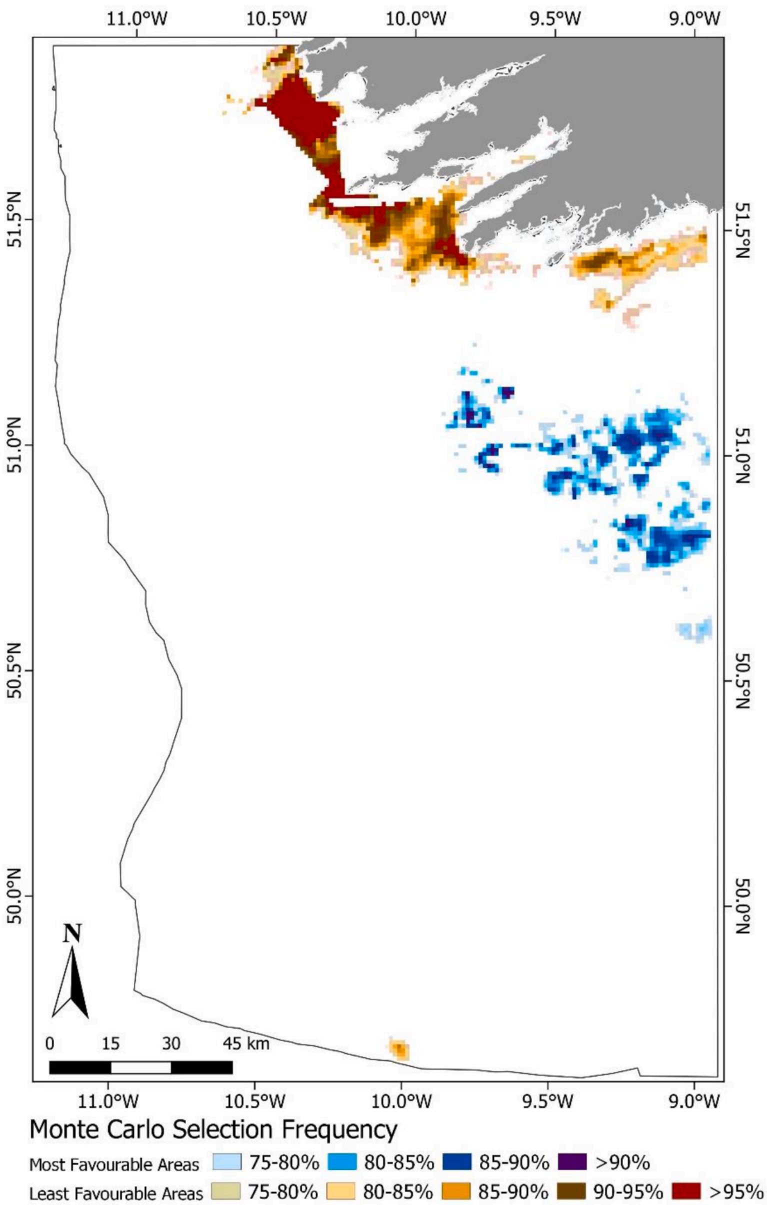

Fig. 9. Selection frequency results of 10% most and least favourable areas for offshore wind development based on 1,000 Monte Carlo simulations.

5. Discussion

Research employing AHP to quantify complex decisions and maximise objectivity is abundant in the available literature (e.g. Azizkhani et al., 2017; Chamanehpour et al., 2017). These studies often adjust scores to achieve adequate consistency ratios, which is a necessary aspect of the analysis (Saaty, 1987). However, some studies do not explain if or how CRs were corrected (e.g. Şener et al., 2010; Uyan, 2013) and mechanisms for introspection that would facilitate meaningful bias reductions are even rarer.

5.1. How do disparities in expert opinion arise and how are they best compensated?

The survey responses from our panel of 25 experts revealed that variations in what criteria were considered important to offshore wind farm developments were common and that judgement discrepancies from individual experts were also prevalent for single variables when comparing intuitive ranking (IPA assessments) with a ranking via relative pairwise values (for AHP). This latter observation reaffirms the importance of a systematic approach to decision making, like the AHP. However, while the general utility of AHP is not in question, the way it is applied to complicated subjects like renewable energy development currently does not represent the wide range of interested parties and expert opinions suitable for such a socially impactful technical transition. Unfortunately, the variability of the AHP-derived criteria weights in this study is shown to be significant; in some instances, such as the importance of the wave criteria, results ranged from 1.2 – 43.6% (Fig. 4, SI2).

Considering the inconsistency in the expert responses, the use of AHP may enable the underlying opinions that inform pairwise-comparison assessments to appear more objective than they really are — essentially clouding inherent bias with well-intentioned maths. This does not necessarily devalue previous research or disparage efforts to quantify opinion; any rigorous application of AHP is likely an improvement over more intuitive judgements (as shown by our IPA results; Fig. 5, Table 2). However, it should be noted that the best mathematical treatment to the judgments of any individual does nothing to reduce or remove biases. Therefore, algorithmic consistency improvements can potentially disguise biases by cultivating a false sense of objectivity through the implication of inerrant mathematics without addressing the foundation of subjective opinion on which the maths rely. AHP derived weights can be perfectly consistent yet subjective. The mathematical treatment of survey responses returned acceptable CRs for all expert opinions that include outliers (Fig. 4) but, ostensibly, bias of experts, perhaps towards their own field of research, persisted. For instance, the outlying survey respondents that overprioritised biology, depth, and waves (Fig. 5and 8C-E) were academic experts that reported expertise in the fields of ecology, oceanography, and engineering, respectively. Their concerns regarding these criteria's importance to offshore wind development potential based on subject-specific expertise are valuable and should have bearing on the decision-making process. However, it is integral to temper bias and convene a balanced group of experts with input from academia, industry, and the public, to account for a broad spectrum of opinions sufficient to contribute to innovative societal transitions while achieving some level of objectivity. Dawes (1979) asserted that human judgement is more adept at selecting information than integrating disparate data. However, bootstrapping models of expert judgements can catch the essence of expertise while reducing unreliability (Dawes, 1979). To this end, the parametric bootstrap implemented here through a stochastic Monte Carlo approach lends itself to establish trends in the data and build confidence that significant technological and societal transitions are based on the best available knowledge.

5.2. What are the effects on geospatial MCDAs and implications for the renewable energy transition?

Despite our findings, it is commonly argued that the use of AHP can reduce subjectivity (e.g. Vagiona and Kamilakis, 2018; Vasileiou et al., 2017) and often only the authors' judgement(s) are used for weighing a geospatial MCDA for renewable energy developments (Chamanehpour et al., 2017; Pınarbaşı et al., 2019; Vagiona and Kamilakis, 2018; Vasileiou et al., 2017). This is concerning because the presented results suggest that subjective, biased judgements are common when experts are compared to their peers. Any one of the experts surveyed for this study could be considered sufficiently knowledgeable for a stand-alone AHP assessment, thus, any of the outliers presented here (Fig. 4) would be sufficient to inform weights in a geospatial MCDA, thereby rendering each geospatial result presented in Fig. 8 equally viable for informing development potential.

Such arguments are built on the misconception that this was a single-decision maker's problem' while as a multi-disciplinary task integral to the renewable energy transition, it is better approached as a group-decision making process. Nonetheless, in the literature of GIS-MCDAs (non-specific to renewable energy) 79.5% of studies employed individual rather than group decision-making (Malczewski, 2006). Ho et al. (2018) are amongst the only to solicit expert opinion to reach consensus about offshore wind farm criteria using the Delphi method. Their results from a consultation with international experts from 10 countries identifies criteria of lesser and greater importance on the Likert scale, and quantify the consensus or dissensus amongst experts through two iterations of a Delphi survey. Some criteria, such as the 'distance from coral reefs' that was considered very to extremely important with the highest degree of consensus (Ho et al., 2018), has relatively little bearing on countries that do not have such habitats. Country-specific surveys with experts who understand the circumstances and environment in the relevant jurisdiction are thus required. The presented AHP weightings must therefore be viewed in the context of the local environment and socio- and techno-economy. Building on the framework of profitability, social, security and environmental selection criteria for OWF sites scored on the Likert scale (Ho et al., 2018), the AHP enables the attribution of relative priorities to the factors influencing the designation of development zones that can be incorporated in a GIS-MCDA.

The widespread method to use only authors' judgements in the AHP to derive weights for planning processes of such magnitude is misleading and needs to give way to a more inclusive approach involving numerous experts and opinions in the decision-making process. This amounts to a paradigm shift that can foster broader support for the renewable energy transition. Not in my backyard

(NIMBY) attitudes and concerns for local environmental impacts have contributed to but are not the sole cause of public resistance to renewable energy developments (e.g. Westerberg et al., 2015; Wolsink, 2007), and improving procedural fairness in decision making of energy infrastructure projects is critical to their success (Wolsink, 2007; Segreto et al., 2020). Several factors of the integrated acceptance model for wind energy (Hübner et al., 2023) have a spatial dimension, which can be addressed in the early planning phase. Marine planning processes frequently involve the public and a broad group of experts at a consultation stage when spatial preferences have already been established. Introducing an inclusive mechanism to set priorities such as the one demonstrated here at the beginning of the planning process would increase participation and support amongst stakeholders. Further improvements should be sought to converge towards group decision consensus using the AHP, which has received less attention in the literature than consistency of an individual's AHP judgements (Dong et al., 2010) though recent advances provide an increased number of operational implementations (e.g. Moreno-Jiménez et al., 2008; Dong et al., 2010; Aguarón et al., 2016, 2019).

5.3. What is the significance for Irish marine planning & energy policy?

With OWE required to contribute 12–35% of sustainable electricity to the Irish grid by 2030 (EirGrid, 2019), a number likely to increase substantially in the 2030s, there is an undeniable demand for space to accommodate OWFs in Irish waters. The steeply sloping nature of the Irish seabed provides limited space for fixed foundation developments, which will likely be concentrated to the Irish Sea and installed by 2030 (Cummins et al., 2020). On top of the unfavourable bathymetry for fixed foundations in the south-west of Ireland, the proximity to important bird areas and conflict with shipping lanes highlight the importance of developing floating wind to unlock Ireland's wind energy resource (Fig. 9). A less mature market in floating OWE involving higher LCoE dictates that development potential of the Celtic Sea and Atlantic Ocean within the Irish EEZ will only be realised in the medium to long term. However, the increased costs of developing floating offshore wind at greater costs and distances from shore necessitates careful planning by the state to enable this nascent industry. This will entail strategic investment in national infrastructure projects to provide grid connections, a road network and ports to support an industry at the scale required to make offshore wind profitable (Cummins et al., 2020). Given the enormous challenge society faces to complete the renewable energy transition, it is paramount to garner public support and involve all stakeholders from the onset, especially where infrastructure decisions affect declining coastal communities. While the proposed group decision-making process using the AHP to inform priorities for spatial planning does not replace a licensing, consultation, and consenting processes, it should form a cornerstone of the planning framework. The outcome of OWE opportunity mapping should also be balanced with the needs of other emerging sectors, such as aquaculture and wave energy developments in an integrated approach to MSP (e.g. Lester et al., 2018).

On top of guiding strategic investment, the results from a Monte Carlo-MCDA based on synthesised priorities of a diverse group of experts, members of the public and stakeholders could be used to outline offshore wind development zones, within which developers bid to install OWFs. Such a planning exercise should ideally be conducted for the entire domain of the Irish EEZ within the depth range of floating turbines. While more elaborate LCoE modelling would provide better estimates of economic aspects, there is considerable benefit to MCDA in accounting for hedonic values such as people's visual appreciation for seascape as well as ecosystem services associated with biological features. Sufficient industry expertise is required in the group-based weighting of criteria to ensure the economic feasibility of development areas, however, there will invariably be further requirements for surveys and cost-analysis in the site selection process. Numerous studies have dubbed similar broad-scale MCDAs 'site-selection' investigations (e.g. Cradden et al., 2016; Chaouachi et al., 2017; Saleous et al., 2016), yet the method is more suited to identifying general 'development zones'. The renewable energy transition will benefit from the government opening broad offshore wind development zones to competitive bids of renewable energy companies that are best placed to identify OWF sites within zones based on development potential and project cost optimization. A similar approach was taken by the UK since the third round of offshore wind energy tenders (Mytilinou et al., 2018), though the more advanced group-based approach to weighing an MCDA has the potential to streamline and accelerate consenting and licensing. This in turn may allow Ireland and other nations to catch up with more advanced offshore renewable energy markets.

6. Conclusion

Transitioning to renewable energy has been set as a critical goal by many research institutions and governments. Europe has emerged as one of the global leaders in this transition (Peters et al., 2020d), however progress has been inconsistent. As a relative late mover in OWE, Ireland, and many other nations that are only beginning to avail of or plan for offshore renewable energy generation, have an opportunity to learn from the pitfalls of decision-making processes for offshore renewable energy siting in other jurisdictions and capitalise on their lessons to progress quickly through the renewable energy transition. These 'follower' countries must adopt technological innovation systems to their individual needs and conditions, which inevitably requires the involvement of experts on the local context and mediation between their potentially incongruous judgement.

Multi-criteria analyses rightfully play an important role in guiding decisions and planning developments for renewable energy projects. AHP-derived weights for the disparate factors in these assessments are common and provide quantifiable results for otherwise incompatible considerations. However, the present study clearly demonstrates the high levels of subjectivity involved with AHP-derived weights, despite rigorous mathematical treatment of the individual comparisons. Individuals' bias significantly affects the results of MCDAs, and therefore the selection of offshore wind development zones. It is thus imperative to treat this geospatial optimization task as a group decision problem, whereby the determination of criteria priorities must stand at an early stage of the planning process. Large-scale renewable energy projects required for transitioning to sustainable electricity risk being perceived as *fait accompli* at the consultation stage. This, in turn can hinder transitions to more responsible environmental technologies and associated benefits like economic returns and environmental health. AHP group decision-making can facilitate a shift in planning to a bottom-up approach, increasing public support and reducing development costs by refining interest areas and improving consentability.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Anonymised data has been attached as an e-component at the submission stage.

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Supplementary materials

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