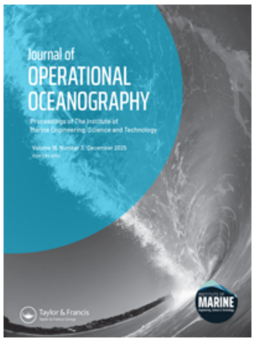

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Comparison of reanalysis datasets with historical wave buoy data in northern Scottish waters

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ABSTRACT
Wave data are critical for assessing marine-energy potential, designing offshore infrastructure, and planning operations and maintenance activities. In regions where interest in renewable energy development is rapidly growing, reliable long-term wave datasets are essential. This study evaluates the reliability of four ocean-wave reanalysis models, ECHOWAVE, ERA5, WAVEWATCH III, and Copernicus Global Ocean Waves Analysis and Forecast, by comparing them to in-situ wave buoy measurements collected between 2011 and 2015 at multiple locations around northern Scotland. The study focuses on the reliability of long-term wave reanalysis datasets in a geographically specific and energy-relevant region. We show that all four models correlate well with observed data, with notable improvements in bias reduction compared to earlier generations of wave modelling. ECHOWAVE consistently demonstrated the closest statistical agreement with buoy data, particularly in nearshore environments. While all models tended to under-estimate or over-estimate significant wave heights during large wave events exceeding 8 m significant wave height, ECHOWAVE's high-resolution modelled data proved especially robust. These findings support robust use of modern reanalysis datasets, especially ECHOWAVE, for wave energy exploration and marine planning. Continued refinement of wave reanalysis models enhances their value as reliable tools for long-term environmental assessment in regions poised for renewable energy expansion.

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Wave energy; extreme events; weather windowing; North Sea

Introduction

The north of Scotland has gained recognition as a leading hub for offshore and marine renewable energy. Over the years, extensive testing and commercial deployments have taken place (Scotland National Marine Plan 2015). The region has witnessed the deployment of the MeyGen array of tidal stream turbines in the fast tidal waters of the Pentland Firth, testing of wave energy converters and the development of large offshore wind farms (Coles et al. 2021; Isaksson et al. 2023).

Wave, tidal, and wind energy projects rely on wave data to understand the potential for wave energy extraction, or to understand the wave environment for the design of marine structures and energy converters, and to plan operations and maintenance. The IEC standard, IEC TS 62600-101 (2024), specifically addresses the requirements for wave energy resource assessment and characterisation, stating that a 10-year dataset is essential for characterising wave conditions during site reconnaissance, feasibility studies, and design processes. In-situ buoys are a traditional method for the collection of wave data, however other methods for wave data collection are available (Rossi et al. 2022). Historical instrument data of such durations are often not available for specific locations of interest; therefore, alternative approaches involve utilising modelling techniques or global reanalysis datasets to complement in-situ measurements. Reanalysis models are regional or global modern weather forecasting models which are calibrated using available observational data (Mistry et al. 2022).

Global wave datasets have been available for several decades (Cotton and Carter 1994), with continuous improvements driven by advances in physical parameterizations, numerical schemes, and atmospheric forcing fields (Jiang et al. 2023). These enhancements are exemplified by the development of semi-empirical dissipation source functions that better represent wave energy loss due to breaking and turbulence (Ardhuin et al. 2010), and by improved understanding of wave breaking distributions (Romero 2019), which inform model calibration. Numerical advancements, particularly in spectral wave models, have also contributed significantly to model accuracy in coastal and open-ocean settings (Roland and Ardhuin 2014). Furthermore,

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efforts to refine wind and wave field representations in regional basins have highlighted the importance of accurate forcing fields for reliable wave predictions (Cavaleri and Bertotti 1997).

As reanalysis models are run using available observational data, and differ in temporal and spatial resolution, comparison to any in-situ data will give an estimate of the model's accuracy in that region. Global wave reanalysis datasets have been compared to collected buoy data previously (e.g. Caires et al. 2004; Shanas and Kumar 2014; Campos and Guedes Soares 2016; de Hauteclocque et al. 2020). Key variables such as significant wave height and extreme wave heights have been found to vary depending on which global model is used (Stopa and Cheung 2014; Sharmar et al. 2021; Morim et al. 2023). It has been found that hazard estimates can change depending on datasets and models adopted, and geographical area of interest (Morim et al. 2023; Hinkel et al. 2021).

This study aims to compare three widely utilised global reanalysis datasets and a recent high-resolution model with historical nearshore wave data collected in the north of Scotland. The wave buoy datasets collected are independent of data used to correct the reanalysis models and have not been used for any bias correction in the reanalysis models. By conducting this comparison, we seek to evaluate the reliability and accuracy of these global reanalysis datasets for the waters around the north of Scotland, a key area for marine renewable energy development, including wave and tidal energy projects where accurate wave climate characterisation is critical for resource assessment, infrastructure design and risk mitigation.

Methods

Data

Datawell 90 cm directional Waverider buoys (DWR-MkIII) were deployed at various locations along northern Scotland, of which four datasets are used here (Table 1 & Figure 1). Wave buoys were deployed with a standard mooring configuration as per the manufacturer's recommendations, with exact configuration dependent on depth and current speed.

Table 1. Wave buoy data sets used in this study.

Buoy name locations	Coordinates	Start date	End date	Distance from land (km)	Depth (m)
Brimms Ness	58.620°N 3.750°W	14-Feb-2013	08-Aug-2013	4.5	45
Bettyhill	58.632°N 4.374°W	02-Oct-2014	24-Aug-2015	20	70
Bragar	58.429°N 6.909°W	19-Sep-2011	31-Mar-2013	16	81
Wick	58.465°N 2.517°W	01-Jan-2012	17-Jul-2012	36	63

Wave conditions in the North Atlantic are seasonal, with relatively small waves in summer and most wave activity during late autumn through to spring. Waves are generated in winter by low pressure systems which mostly follow a west-to-east trajectory along the prevailing extratropical storm track (Semedo et al. 2008), with the latitude of the storm track influenced by the position of the jet stream (Harvey et al. 2020).

The following reanalysis model data were compared to the wave buoy datasets:

- ECHOWAVE: (European COasts High Resolution Ocean WAVEs Hindcast) developed by Marine Renewable Energies Lab (MREL), TU Delft Available at: https://metocean-api.readthedocs.io/en/latest/index.html (Alday and Lavidas 2024)
- ECMWF ERA5 global wave reanalysis (ERA5 hourly data on single levels from 1940 to present). Available at: https://cds.climate.copernicus.eu/datasets/reanalysis-era5-single-levels?tab=overview
- WAVEWATCH III Global Wave Reanalysis Model (WW3 Global), from 1999 to present; Listed under 'Archived Data' (WAVEWATCH III version 2.22 Hindcast under the NOAA MMAB FTP server); https://polar.ncep.noaa.gov/waves/ensemble/download.shtml
- Copernicus Global Ocean Waves Analysis and Forecast WAVERYS; https://data.marine.copernicus.eu/product/GLOBAL_MULTIYEAR_WAV_001_032/description

ECHOWAVE is a high-resolution hindcast wave model developed by Alday and Lavidas (2024) to support wave climate and energy applications across the European Atlantic coast. Built using the WAVEWATCH III framework, the model employs a two-way nesting, multi-grid scheme to achieve spatial resolutions down to approximately 2.3 km, particularly in coastal areas with depths less than 200 m. The hindcast spans 1990–2021 at hourly intervals, providing detailed spectral and integrated wave parameters.

ECHOWAVE incorporates a custom parameterisation (TUD-165) optimised for the North-East Atlantic, significantly improving the accuracy of sea state characterisation compared to previous models like ERA5 and WAVERYS. Validation was conducted using ESA's Sea State CCI V3 altimeter data and in-situ measurements, demonstrating reduced bias in both frequent and extreme wave conditions (Alday and Lavidas

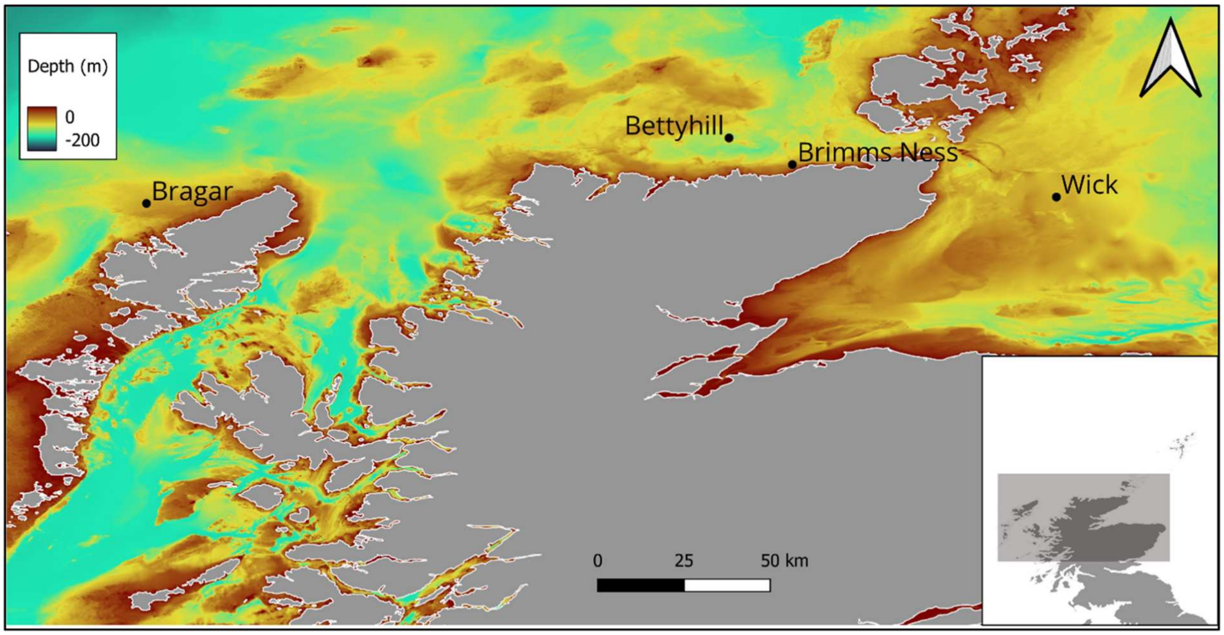

Figure 1. Locations of the wave buoys (circular markers) and bathymetry around study area of north Scotland.

2024). Forcing fields employed are the ECMWF ERA5 wind fields defined at 10 m above sea level. The model has 36 frequency directions and 36 frequencies, from 0.034 to 0.95 Hz with output wave parameters with a temporal resolution of 1 h.

The second dataset used is ERA5, the fifth generation ECMWF reanalysis for the global climate and weather with data from 1940 to present. ERA5 has a spatial resolution of 0.5°×0.5° and a temporal resolution of 1 h. The two parameters studied for this dataset are the significant height of combined wind waves and swell, and the mean wave period (Hersbach et al. 2020). ERA5 reanalysis atmospheric forcing fields are employed. The model has a directional frequency resolution of 24 directions, 30 frequencies (0.0345–0.547 Hz). The model output is hourly wave statistics. The model has 4D-Var assimilation of satellite and in-situ observations into the atmospheric model, which drives the wave model.

The third dataset is WAVEWATCH III, the third-generation wave model developed at NOAA/NCEP (Tolman 1989). This dataset has a spatial resolution of 0.5°×0.5° and a temporal resolution of 1 h. The two parameters chosen for this dataset are significant wave height and peak wave period. The model has forcing fields of NCEP operational winds and ice fields. The directional frequencies are 24 directions and 30 frequencies (logarithmically spaced). Output fields have a 3 hourly statistical temporal resolution.

The fourth dataset analysed is the Global Ocean Waves Analysis and Forecast (WAVERYS), product id: GLOBAL_ANALYSISFORECAST_WAV_001_032, describing past sea states since 1993 (Zhang et al. 2024). The spatial resolution is approximately 0.2°×0.2° and the temporal resolution is 3 h. The model employs forcing fields of 6-hourly analysis and 3-hourly forecast winds from ECMWF IFS. The model has a directional / frequency resolution of 24 directions and 30 frequencies and has data assimilation of satellite altimeter wave height data.

The selection of ECHOWAVE, ERA5, WAVEWATCH III, and WAVERYS for this study was guided by their widespread use, data availability, and relevance to wave energy applications. These models represent a diverse range of wave modelling approaches, including global reanalysis products with data assimilation (ERA5 and WAVERYS), an operational third-generation spectral wave model (WAVEWATCH III), and a high-resolution regional model tailored for UK waters (ECHOWAVE). All four provide long-term datasets suitable for resource assessment.

As stated, the model data were not interpolated, rather the nearest grid data point was used to avoid any bias with points over land. The grid points used are shown in Table 2.

The grid points used (Table 2) correspond to distances from the relevant wave buoy position shown in in Table 3.

Data processing

Datawell wave buoy data were pre-processed with the Datawell proprietary ‘Waves5’ software (Datawell BV

Table 2. Grid points (latitude and longitude in degrees) associated with the models.

Site	Buoy lat.(°)	Buoy lon.(°)	ECHOWAVE lat.(°)	ECHOWAVE lon.(°)	WAVERYS lat.(°)	WAVERYS lon.(°)	ERA5 lat.(°)	ERA5 lon.(°)	WW3 lat.(°)	WW3 lon.(°)
Brimms Ness	58.62	−3.75	58.62	−3.75	58.6	−3.8	59	−4	59	−4
Bettyhill	58.632	−4.374	58.62	−4.38	58.6	−4.4	59	−4	59	−5
Bragar	58.429	−6.909	58.44	−6.9	58.4	−7	58	−8	58.5	−7
Wick	58.465	−2.517	58.47	−2.52	58.4	−2.6	58	−2	58.5	−2.5

2019). The software generates statistical datasets from the raw wave buoy heave data which are used here. Bad data were identified in the Waves5 software and removed. Two spikes were detected during two large storm events in the Bragar dataset; no spikes were detected in the other wave buoy datasets. The spikes consisted of a sudden increase in significant wave height over one half-hour period, for example from 10 m Hs to over 16 m Hs between two half-hour recordings during 18th January 2012. The Waves5 software flagged that there was a problem with the data at each of these spikes. On inspection of the raw heave data, large and sudden increases in negative and positive heave were recorded. This is indicative of breaking waves impacting on the wave buoy accelerometers (Dhoop et al. 2024). The data spikes were not removed for this analysis and it was noted that they did not statistically affect the comparisons.

The resulting statistical 'HIS' data files contain ½ hourly statistics including significant wave height and peak period, amongst others. Data for the same time periods as the wave buoy datasets were subset from the reanalysis datasets. Statistics were calculated to compare the reanalysis datasets to the wave buoy datasets. Two variables, the significant wave height (i.e. total sea, Bessonova et al. 2025), and the mean period (peak period for the WW3 model), were compared.

Calculations of skill metrics for mean, standard deviation and correlation coefficient R^2, root mean squared error, scatter index and symmetric mean absolute percentage error were calculated for each parameter of each dataset.

The grid cell closest to each wave buoy position was selected from each reanalysis dataset. For calculation of the correlation coefficient, the temporal resolution of each dataset (reanalysis and buoy) was required to be equal. Linear interpolation of the reanalysis data was performed to match the temporal resolution of the wave buoy dataset of half-hourly intervals (Zhang et al. 2024). Bias for significant wave height was also investigated between each reanalysis and buoy dataset. For the bias, the significant wave height data from each reanalysis dataset was subtracted from the wave buoy data. The resultant bias of significant wave height was binned into twenty bins and graphed. Histogram plots were simplified for presentation by plotting a line through the centres of each bin count for each.

Table 3. Distances to the model grid points from the buoy positions.

Site	ECHOWAVE (km)	WAVERYS (km)	ERA5 (km)	WW3 (km)
Brimms Ness	0	3.66	44.73	44.73
Bettyhill	1.38	3.87	46.34	54.67
Bragar	1.33	6.22	79.97	9.53
Wick	0.58	8.71	60.04	4.02

Results

Results of statistical analysis comparing the four wave models – ECHOWAVE, WAVERYS, ERA5, and WW3 – to buoy data are presented in Table 4–6 for each comparison parameter. Model performance was evaluated at four coastal sites in northern Scotland using a suite of statistical metrics: correlation coefficient (R^2), standard deviation (stdev), root mean square error (RMSE), scatter index (SI), and symmetric mean absolute percentage error (SMAPE).

At Bettyhill, ECHOWAVE demonstrated superior accuracy with $R^2 = 0.956$ and RMSE = 0.30 m, outperforming all other models. WAVERYS showed reasonable performance ($R^2 = 0.93$), but with elevated error levels (RMSE = 0.53 m; SMAPE = 9.68%). ERA5 and WW3 exhibited reduced skill, with WW3 showing the lowest R^2 and highest RMSE (1.13 m) and error metrics.

At Brimms, ECHOWAVE maintained high skill ($R^2 = 0.95$; RMSE = 0.31 m), with WAVERYS following ($R^2 = 0.87$). ERA5 and WW3 were associated with higher RMSE and SMAPE values, suggesting poorer performance in replicating observed wave conditions.

At Bragar, both ECHOWAVE and WAVERYS exhibited strong agreement with observations ($R^2 \geq 0.95$). ECHOWAVE yielded the lowest RMSE and SMAPE, indicating improved fidelity compared to other models. ERA5 and WW3 trailed, though WW3 showed a relatively higher R^2 (0.92) than at other sites.

At Wick, WAVERYS achieved the lowest RMSE (0.25 m) and SI (18.98%), suggesting strong

Table 4. Mean values of significant wave height and period for each buoy dataset and reanalysis dataset. (Peak period only available from WW3 data.)

	Mean significant wave height (m)					Mean wave period (s)				Peak wave period (s)	
	Buoy	ERA5	WW3	WAVERYS	ECHOWAVE	Buoy	ERA5	WAVERYS	ECHOWAVE	Buoy	WW3
Brimms Ness	1.44	1.88	1.80	1.23	1.50	6.73	7.75	7.86	6.43	10.17	9.69
Bettyhill	2.16	2.80	3.03	1.84	2.30	6.95	8.65	8.66	7.15	10.72	11.03
Bragar	3.11	2.98	2.95	2.71	3.09	7.64	8.57	9.00	7.68	11.12	10.92
Wick	1.33	1.52	1.35	1.30	1.40	5.21	6.22	5.89	5.03	7.98	6.54

performance despite ECHOWAVE achieving a slightly higher R^2 (0.88). ERA5 performed poorly ($R^2 = 0.59$), with markedly elevated RMSE and scatter index values.

The bias of significant wave height for each reanalysis dataset against buoy data is presented as line plots of histogram results for comparison (Figure 2). Differences in the shapes of the peaks and their spread around the zero bias shows differences between the datasets in comparison to the wave buoy data. Central tendency, spread/variability, symmetry, and outliers of biases, indicate how accurate and consistent each wave height model is compared to the reference buoy data.

To visually investigate differences between the reanalysis models and the wave buoy data, the reanalysis datasets were plotted against the wave buoy data as scatter graphs for significant wave height (Figure 3). As the correlation coefficient suggests, the variables show good linear correlation visually, however outliers can be seen, in particular for the Bragar data.

The Bragar data included several large wave periods associated with large storm systems. The largest wave events in the dataset were associated with a deep depression (Figure 4) resulting in large significant wave heights (Figure 5, with QQ plots shown in Figure 6).

Discussion

Comparison of mean values (Table 4) show that ECHOWAVE data aligns most closely with buoy observations for both significant wave height and wave period, suggesting high reliability. ERA5 and WW3 tend to overestimate wave heights and periods, while WAVERYS underestimates wave height but overestimates wave period. Among the locations, Bragar consistently experiences the highest wave conditions, while Wick shows the lowest, in line with more sheltered conditions. Overall, ECHOWAVE appears to provide the most accurate model.

For significant wave height (Table 5), ECHOWAVE consistently outperforms the other models across all metrics, with the highest R^2 and lowest RMSE, SI, and SMAPE. WAVERYS performs well, particularly at Bragar and Wick, but shows higher RMSE and bias than ECHOWAVE. ERA5 and WW3 show the lowest accuracy, especially in capturing wave height variability and extremes, with higher scatter and error metrics.

Wave period estimates across models are generally consistent with buoy data. The standard deviation values (Table 6) suggest comparable variance among the reanalysis datasets, with WAVERYS showing the closest match to buoy data variability. Correlation coefficients (Table 5) highlight WAVERYS as the most accurate model for predicting significant wave height, with a correlation of 0.95 at Bragar and 0.93 at Bettyhill. For mean wave period, WAVERYS also outperforms ERA5. WW3 shows the lowest correlation for peak wave period, indicating limitations in capturing short-term wave dynamics.

Bias analysis (Figure 2) reveals similar patterns between ERA5 and WAVERYS, though ECHOWAVE exhibits a narrower peak and lower bias across all sites, particularly at Brimms Ness and Bettyhill. This supports the conclusion that ECHOWAVE has the best overall agreement with buoy data, consistent with correlation findings. However, histogram tails and scatter plots (Figure 3) reveal outliers, most notably in the Bragar dataset. The newly introduced ECHOWAVE model demonstrates superior performance across all sites. It achieves the highest correlation coefficients, lowest RMSE, and lowest bias in both wave height and wave period metrics (Tables 4-6). For example, at Bragar, ECHOWAVE achieves an R^2 of 0.96 and a SMAPE of just 4.01%, outperforming all other models for significant wave height. These results suggest that ECHOWAVE provides a more reliable representation of wave conditions, particularly in regions with complex coastal dynamics and frequent storm activity.

The Bragar buoy, located on the west coast of Lewis, recorded high wave events, including a 10 m significant wave height on 18 January 2012 during Storm David, and a 14 m wave on 4 February 2013. On 4 February 2013, for the Bragar buoy data, ECHOWAVE and WW3 have the closest agreement wave heights during large wave events, with ECHOWAVE having a slight overestimation (Figure 5), while WAVERYS and ERA5 underestimate the significant wave height. It is

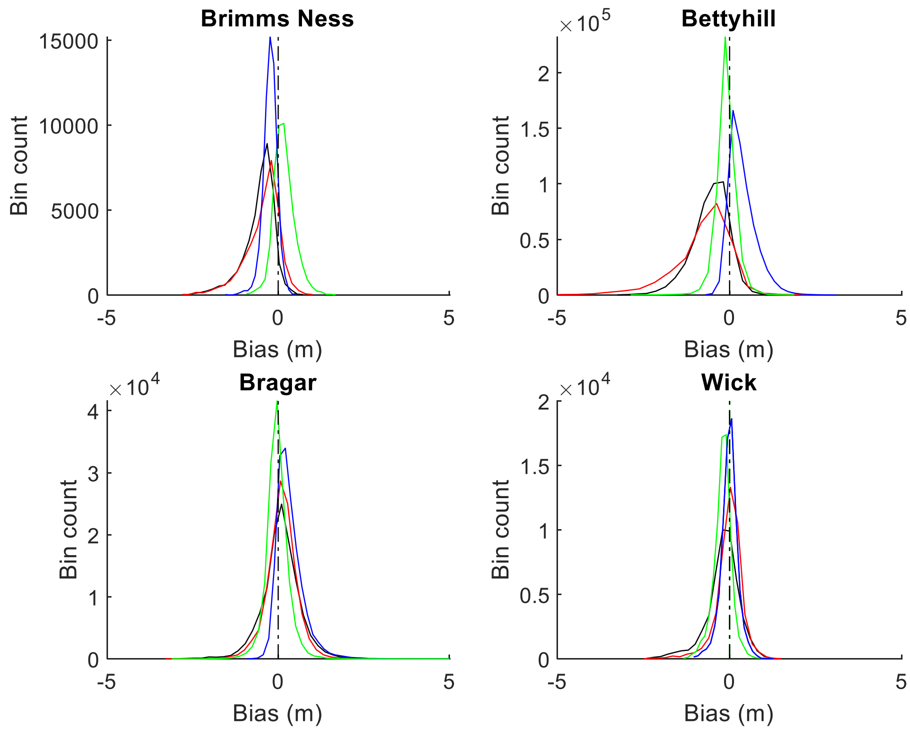

Figure 2. Normalised histograms on the same x axes, each using 20 bins and representing the distribution of biases between buoy reference significant wave heights and reanalysis datasets, ERA5 (black line), WW3 (red line), WAVERYS (blue line) and ECHOWAVE (green line).

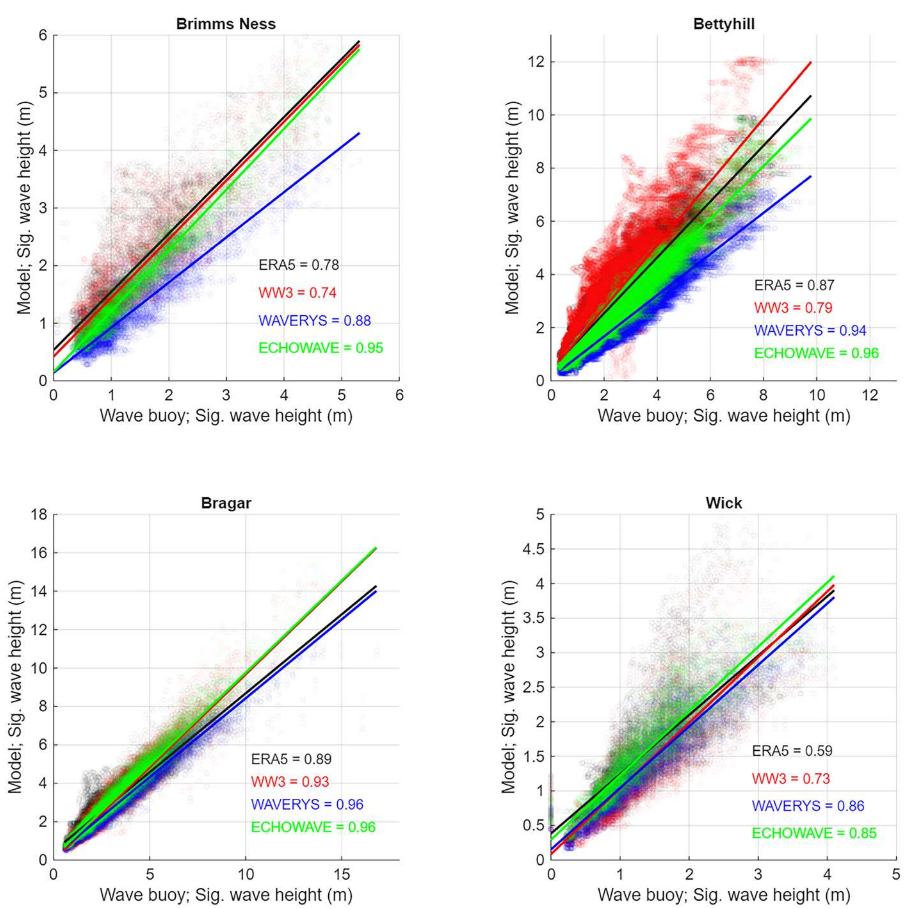

Figure 3. Scatter plots of significant wave height from buoy data compared to reanalysis data showing ERA5 (black), WW3 (red), WAVERYS (blue) and ECHOWAVE (green). For additional clarity, a separate plot per site and per reanalysis and model dataset is provided in the Supplementary Material.

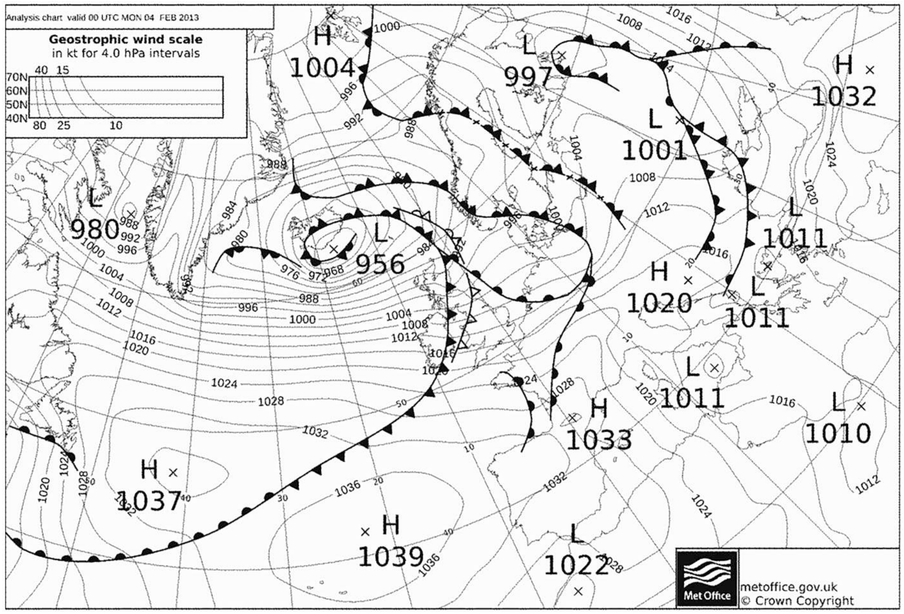

Figure 4. Synoptic pressure chart from the 4th February 2013 (Met Office). Historic reanalysis data. [accessed date 2023 July]. https://www.wetterzentrale.de/

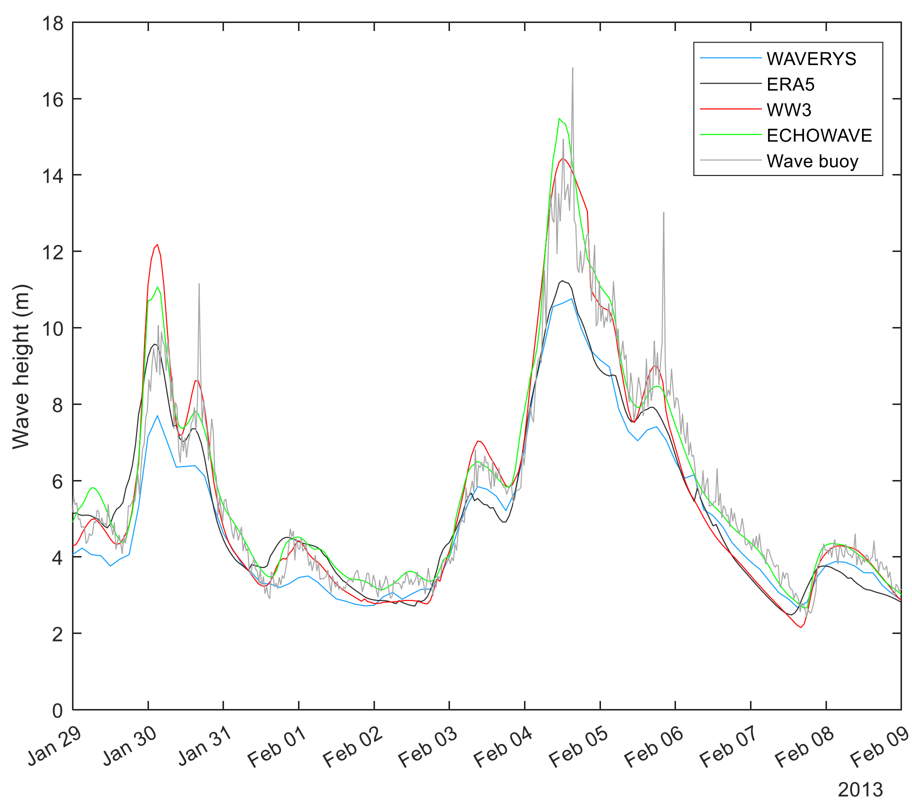

Figure 5. Significant wave height from wave buoy data and the four reanalysis datasets during storm event 4th February 2013 for the Bragar wave buoy.

noted during this particular event, two spikes resulting in a rapid increase in significant wave height recorded may have been due to instrument errors caused by breaking waves affecting the buoy accelerometers due to extreme conditions.

These discrepancies are reflected in the Q-Q plots (Figure 6), with ECHOWAVE showing a slight overprediction under large wave events whilst for the other locations, and lower wave conditions, ERA5 tended to overpredict wave heights, and GOWR showed the best

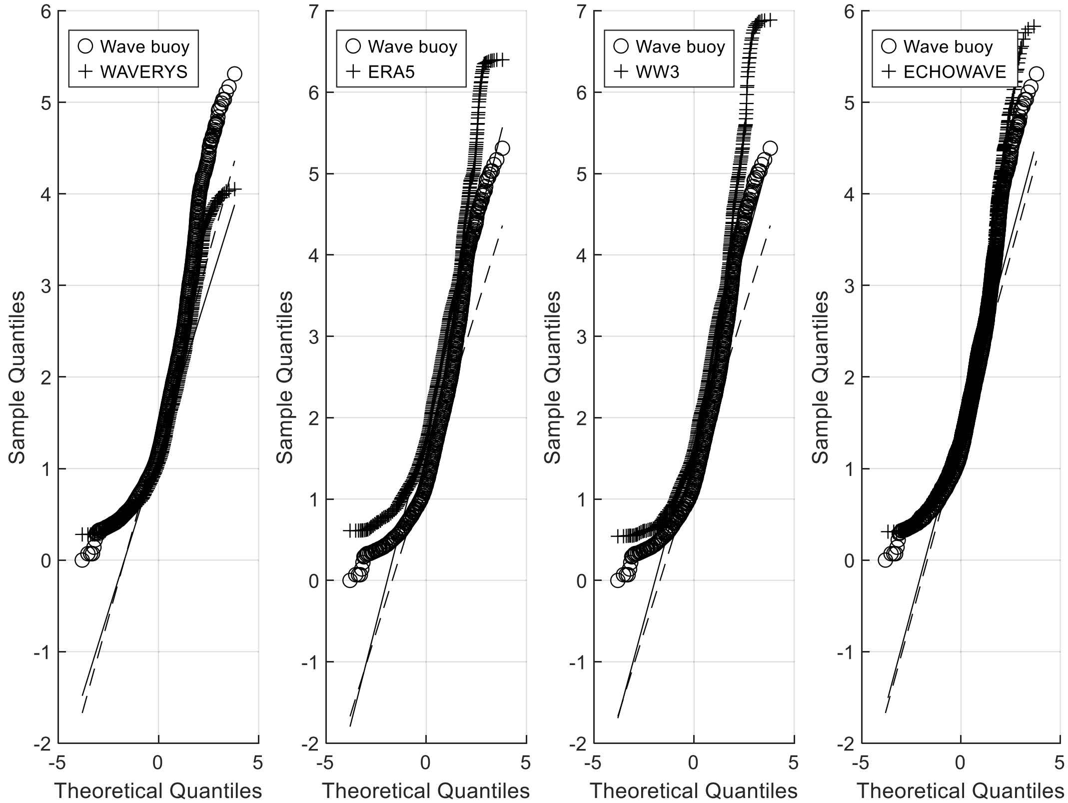

Figure 6. QQ plots for the Bragar wave buoy against the reanalysis and model datasets. The x-axis shows dimensionless standard quantiles and y-axis shows dimensionless z-scores. The solid line shows buoy data, the dashed line shows model/reanalysis data.

fit. The presence of fast-moving storms in the North Atlantic may explain some of the temporal mismatches between reanalysis and buoy data, particularly at Bragar. The coarse temporal resolution of reanalysis models may miss short-lived extreme events, a limitation previously noted in other studies (Shanas and Kumar 2014; Satish et al. 2016; Neary et al. 2020). Additional factors such as wind field accuracy, wave interaction complexity, and local wave breaking processes may also contribute to under or overprediction.

In this region, wave-height modulation by tides is experienced in stronger currents; whilst this effect was deemed to be insignificant for the comparison here, strongly dominated tidal areas such as close to the

Table 5. Skill metrics for significant wave height for the wave buoy data and for each reanalysis model for the same time period and closest grid point to the buoy data. Note R^2 is unitless.

Site	Model	R^2	Stdev (m)	RMSE (m)	SI (%)	SMAPE (%)
Bettyhill	ECHOWAVE	0.95	1.31	0.29	13.65	5.5
	WAVERYS	0.93	1.03	0.53	24.64	9.68
	ERA5	0.86	1.46	0.76	35.34	13.66
	WW3	0.78	1.72	1.13	52.33	16.75
Brimms	ECHOWAVE	0.95	0.91	0.31	21.75	9.55
	WAVERYS	0.87	0.71	0.35	24.43	10.26
	ERA5	0.78	0.97	0.85	49.83	18.39
	WW3	0.74	1	0.68	47.5	16.07
Bragar	ECHOWAVE	0.96	1.6	0.33	10.84	4.01
	WAVERYS	0.95	1.39	0.53	17.11	6
	ERA5	0.88	1.45	0.58	18.66	6.94
	WW3	0.92	1.67	0.47	15.16	6.07
Wick	ECHOWAVE	0.88	0.68	0.33	25.13	10.05
	WAVERYS	0.86	0.64	0.25	18.98	7.55
	ERA5	0.59	0.75	0.52	39.82	12.95
	WW3	0.72	0.75	0.39	29.69	10.52

Table 6. Skill metrics between mean period (*peak period only available from WW3 data) from wave buoy data (peak period for WW3 comparison).

Site	Model	R^2	Stdev (s)	RMSE (s)	SI (%)	SMAPE (%)
Bettyhill	ECHOWAVE	0.89	1.78	0.59	8.54	4.8
	WAVERYS	0.85	2.06	1.86	26.75	10.85
	ERA5	0.83	1.82	1.81	26.14	10.8
	WW3*	0.56	2.9	2	19.22	6.51
Brimms	ECHOWAVE	0.8	1.4	0.67	9.97	3.7
	WAVERYS	0.76	1.68	1.63	24.09	9.67
	ERA5	0.69	1.56	1.6	23.73	9.53
	WW3*	0.37	2.75	2.9	22.49	8.38
Bragar	ECHOWAVE	0.89	1.54	0.52	6.8	2.75
	WAVERYS	0.85	1.63	1.59	20.77	8.97
	ERA5	0.84	1.61	1.2	15.77	6.62
	WW3*	0.56	2.57	1.83	16.45	5.34
Wick	ECHOWAVE	0.73	0.92	0.53	10.41	3.98
	WAVERYS	0.68	1.17	1.05	20.62	7.89
	ERA5	0.5	1.19	1.4	27	9.97
	WW3*	0.2	2.1	2.6	32.8	13.27

Note: R^2 is unitless.

Pentland Firth will have strong wave modulation and therefore in-situ data may have larger deviation from the reanalysis models which do not typically include such effects.

While reanalysis datasets remain invaluable for long-term wave climate assessments, developers of marine renewable energy projects should be aware of their limitations in capturing extreme wave events. However, continual improvement in reanalysis models such as high-resolution models like ECHOWAVE show high correlation to in-situ datasets in this locality and are highly suitable for long term wave energy and risk assessment in intermediate waters.

Conclusion

Data collected from four wave buoys along the north of Scotland were compared with reanalysis models. Of the reanalysis models compared, the ECHOWAVE model had the highest statistical similarity to the wave buoy data for the wave height and wave period variables. ECHOWAVE, ERA5 and WAVERYS showed disagreement in some form during extreme events such as those from the Bragar wave buoy dataset, which may be in part due to the temporal resolution of the datasets amongst other factors. For extreme wave heights, the WW3 reanalysis showed the best predictions but still under predicted in comparison to the wave buoy data in moderate conditions.

For the selected wave buoy data and reanalysis products, WAVEWATCH III reanalysis data performed the best in extreme wave conditions, suggesting it may be better suited for calculations involving the prediction of extreme wave heights over certain period ranges such as 1, 10 and 50 years as suggested by IEC standards. Based on the correlation results and performance of the models at all sites, the ECHOWAVE reanalysis model was the most accurate and well suited to long-term wave statistics in the North of Scotland in near shore conditions for renewable energy developments.

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Disclosure statement

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