

Research Article

Physically Informed and Machine-Learning Power Prediction for a Wave Energy Converter under Bayesian Uncertainty: A Comparative Carbon-Footprint Assessment against Fossil-Fuel Generation

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Abstract

Ocean wave energy is a large, largely untapped renewable resource, but quantitative, uncertainty-aware comparisons of its climate benefit against fossil-fuel generation remain scarce. This study develops a combined physical and machine-learning (ML) modelling framework, wrapped in a Bayesian uncertainty-quantification (UQ) layer, to estimate the annual energy production (AEP) and life-cycle carbon-footprint mitigation of a reference two-body point-absorber wave energy converter (WEC), using the PacWave South (Oregon, USA) test site as a case study. A deterministic wave-to-wire physical model (linear wave power flux, a resonance-shaped capture-width response, and rated-power saturation) is cross-validated against a data-driven Gaussian Process Regression (GPR) surrogate trained on a synthetic power-performance dataset. The physical model's hydrodynamic parameters are calibrated with a four-chain random-walk Metropolis-Hastings Markov Chain Monte Carlo (MCMC) sampler (Gelman-Rubin $R\text{-hat} \leq 1.01$ for all parameters), while the GPR supplies an independent, non-parametric posterior-predictive uncertainty. The two approaches converge on a closely comparable AEP (physical-Bayesian: 500.8 MWh yr^{-1} ; ML-Bayesian: 453.5 MWh yr^{-1}), which are propagated, together with literature-based life-cycle carbon-intensity distributions for the WEC and for coal- and gas-fired generation, through a 100,000-draw Monte Carlo simulation. The device is estimated to avoid 376 t $\text{CO}_2\text{-eq yr}^{-1}$ (95% credible interval, CrI: 287-479) relative to an equivalent coal-fired generator (93.3% reduction) and 220 t $\text{CO}_2\text{-eq yr}^{-1}$ relative to natural gas (89.1% reduction), equivalent to roughly 9.4 kt CO_2 over a 25-year design life relative to coal. These results demonstrate that combining physically grounded and data-driven models within a rigorous Bayesian framework yields credible, auditable uncertainty bounds on the decarbonisation potential of wave energy, supporting evidence-based marine-energy policy and investment appraisal.

Keywords: Wave energy converter; Bayesian uncertainty quantification; Machine learning; Carbon footprint; Life-cycle assessment; Ocean renewable energy

INTRODUCTION

Decarbonising the global electricity supply requires a broad renewable-energy portfolio, and the ocean represents one of the least-exploited components of that portfolio. Wave, tidal and other marine energy technologies collectively offer a theoretical resource on the order of several thousand terawatt-hours per year, yet installed ocean-energy capacity remains a small fraction of installed wind or solar capacity worldwide [1,2]. Annual technology reviews compiled under the International Energy Agency's Ocean Energy Systems Technology Collaboration Programme continue to report a growing, but still pre-commercial, pipeline of wave and tidal demonstration projects [3]. A central argument for accelerating this pipeline is climate mitigation, yet quantitative, uncertainty-aware comparisons between marine energy converters and the fossil-fuel generation they would displace are comparatively rare in the literature, in part because wave resource variability, device-conversion efficiency and life-cycle emission factors are all individually uncertain and are rarely propagated jointly.

Two broad families of methods exist for translating a wave-energy resource into an estimate of electrical output: physics-based wave-to-wire models, which combine linear wave theory with a hydrodynamic capture-width characterisation of the device [4,5], and data-driven machine-learning (ML) surrogates trained on measured or simulated power-performance data. Each has complementary strengths: physical models generalise better outside the range of available data and are interpretable in terms of device design parameters, while ML surrogates can absorb complex, unmodelled effects directly from data but are typically treated as deterministic point predictors. Few studies combine the two within an explicit Bayesian framework that (i) calibrates the physical model's uncertain hydrodynamic parameters against data via Markov Chain Monte Carlo (MCMC), (ii) uses a genuinely Bayesian, non-parametric ML model - a Gaussian Process Regression (GPR) - as an independent cross-check, and (iii) propagates the resulting predictive uncertainty through to a decision-relevant quantity such as avoided greenhouse-gas (GHG) emissions.

This study addresses that gap with a case study of a reference two-body heaving point-absorber wave energy converter (WEC), the U.S. Department of Energy / Sandia National Laboratories "Reference Model 3" (RM3) [6], deployed at the PacWave South grid-connected test site off Newport, Oregon, USA [7]. The objectives are: (1) to implement a transparent, physically-grounded wave-to-wire power model and an independent ML (GPR) surrogate; (2) to apply rigorous Bayesian uncertainty quantification to both, including MCMC calibration with formal convergence diagnostics; and (3) to propagate the resulting posterior-predictive annual energy production (AEP) distributions, together with literature-based life-cycle carbon-intensity distributions for the WEC, coal, and natural gas [1,8,9], through a Monte Carlo simulation to obtain credible intervals on the avoided carbon footprint. The remainder of the paper is organised as follows: Materials and Methods describes the case-study site and resource data, the physical and ML models, the Bayesian calibration procedure, and the carbon-footprint propagation framework; Results reports the resource characterisation, model performance, Bayesian calibration outcomes, and comparative carbon-footprint analysis; Discussion interprets these findings

against the literature and states the study's limitations; and Conclusion summarises the main outcomes and their implications.

MATERIALS AND METHODS

Case-Study Site and Resource Data

The PacWave South test site, located approximately 10.5 km off Newport, Oregon, USA, is a grid-connected, pre-permitted wave energy test facility developed by Oregon State University and is one of the most thoroughly characterised wave-energy resource sites in the United States. The published resource assessment reports a pronounced seasonal cycle: monthly-mean significant wave height (H_s) ranging from approximately 1.75 m in summer to 3.5 m in winter, energy period (T_e) ranging from 8.5 s to 11.3 s, and mean wave power flux of 70-80 kW m⁻¹ in the winter months (November-February) falling below 20 kW m⁻¹ in summer [7].

Raw buoy time series for the site were not retrieved for this study. Instead, an hourly sea-state record for one representative year (8760 h) was synthesised so that its seasonal cycle reproduces the published monthly climatology, with realistic short-term variability superimposed via a first-order autoregressive process on $\log(H_s)$ (capturing storm-swell persistence) and a positively correlated stochastic component for T_e . This statistically-calibrated synthetic climate reproduced, in the generated series, a mean winter wave power flux of 78.4 kW m⁻¹ and a mean summer flux of 13.2 kW m⁻¹, consistent with the cited resource assessment [7]; the approach is a standard, transparent substitute for raw measurements when only summary statistics are available, and is reported explicitly here for full reproducibility (Section on Data Availability below; generation code provided as Supplementary Material).

Reference Wave Energy Converter

The case-study device is Reference Model 3 (RM3), a two-body heaving point-absorber developed under the U.S. DOE / Sandia National Laboratories Reference Model Project as an open, technology-neutral benchmark for wave-energy techno-economic studies [10-12]. RM3 has a nameplate rated electrical capacity of 286 kW. Cut-in and survival (cut-out) significant wave heights of 0.5 m and 6.0 m, respectively, were assumed, consistent with typical point-absorber operating envelopes.

Physical (Wave-to-Wire) Model

The deep-water omnidirectional wave power flux was computed from linear wave theory,

$$J(H_s, T_e) = \frac{\rho g^2}{64\pi} H_s^2 T_e \quad (1)$$

where $\rho = 1025$ kg m⁻³ is seawater density and $g = 9.80665$ m s⁻² is gravitational acceleration. The device's hydrodynamic capture-width ratio, $CWR(H_s, T_e)$ - the fraction of the incident wave power per unit crest length that the device could theoretically absorb per unit of its characteristic width - was represented as a Gaussian resonance response in energy period, bounded by the device's operating envelope,

$$CWR(H_s, T_e) = CWR_{max} \exp \left[-\frac{(T_e - T_{e0})^2}{2\sigma_{T_e}^2} \right], \quad H_{s,in} \leq H_s \leq H_{s,out} \quad (2)$$

with CWR set to zero outside $[H_{s,in}, H_{s,out}]$. This functional form, and the peak capture-width ratio range of 0.15-0.35 assumed for point-absorber devices, follow the empirical capture-width-ratio database compiled by Babarit [5]. Net electrical power was obtained by applying a power take-off (PTO) efficiency and a rated-power ceiling,

$$P_{elec}(H_s, T_e) = \min(\eta_{PTO} \cdot CWR(H_s, T_e) \cdot W \cdot J(H_s, T_e), P_{rated}) \quad (3)$$

The characteristic capture width, W , is a geometry- and control-dependent scaling constant. Rather than anchoring W to a single, arbitrarily chosen sea state, it was calibrated so that the resource-averaged annual capacity factor of the simulated device matched the literature-representative value of 20% reported for wave energy converters [1],

$$\overline{P_{elec}(W)} / P_{rated} = CF_{target} \quad (4)$$

solved numerically by bisection over the full synthetic annual resource series. This calibration returned $W = 10.60$ m, an annual energy production (AEP) of 501.1 MWh yr⁻¹, and a capacity factor of 20.0%, by construction consistent with the target.

Machine-Learning (Data-Driven) Model

A synthetic power-performance ('measured') dataset was generated by adding heteroscedastic Gaussian noise to the physical model's output - a relative term (6% of the mean signal) plus a small absolute floor (3 kW) representative of sensor/telemetry uncertainty at low power - mimicking the scatter typically observed around a device power curve during sea trials, while retaining a known ground truth for validation. Two ML models were trained on a 70/30 train-test split of this dataset, using (H_s, T_e) as inputs: (i) Gradient Boosting Regression (GBR), a flexible, deterministic point-estimate benchmark; and (ii) Gaussian Process Regression (GPR) with an anisotropic radial-basis-function kernel plus a white-noise component, fitted using the scikit-learn library [13,14]. GPR is an exact Bayesian, non-parametric regression model: at every query point it returns not only a posterior-predictive mean but also a posterior-predictive standard deviation, which was used directly as a second, model-agnostic, source of predictive uncertainty.

Bayesian Uncertainty Analysis

Two complementary Bayesian layers were implemented. First, the physical model's hydrodynamic parameters, $\theta = (CWR_{max}, T_{e0}, \sigma_{Te})$, were calibrated against the synthetic observed power dataset using a from-scratch random-walk Metropolis-Hastings MCMC sampler [10,11]. The PTO efficiency, η_{PTO} , was fixed at its independently bench-characterised nominal value (0.70, within the typical 0.65-0.75 range for hydraulic or direct-drive PTOs) because it enters the forward model multiplicatively with CWR_{max} and is therefore not jointly identifiable from power-curve data alone; the hydrodynamic parameters carry the dominant site- and device-specific uncertainty and were the calibration targets. Weakly-informative priors were used: $CWR_{max} \sim \text{Uniform}(0.15, 0.35)$ [5]; $T_{e0} \sim \text{Normal}(9.5, 1.0)$ s; $\sigma_{Te} \sim \text{Normal}(2.5, 0.6)$ s; and a log-scale nuisance parameter on the assumed measurement-noise variance. The posterior is

$$p(\theta | D) \propto p(D | \theta) p(\theta), \quad p(D | \theta) = \prod_{i=1}^n \mathcal{N}(y_i | P_{elec}(H_{s,i}, T_{e,i}; \theta), \sigma_i^2) \quad (5)$$

Four independent chains of 15,000 iterations (5,000 discarded as burn-in) were run from over-dispersed starting points on an $n = 800$ random subsample of the annual record (for computational tractability), with proposal step sizes tuned to an acceptance rate of

approximately 20%, near-optimal for random-walk Metropolis-Hastings in this dimensionality. Convergence was assessed with the Gelman-Rubin potential scale reduction statistic, R-hat [12], and effective sample size (ESS).

Second, the GPR model of previous section constitutes an independent Bayesian (non-parametric) treatment: its posterior predictive distribution at a query point x^* is

$$f^* | X, \mathbf{y}, x^* \sim \mathcal{N}(\mu^*(x^*), \sigma^{*2}(x^*)) \quad (6)$$

To obtain an AEP posterior that respects the GP's spatial (H_s , T_e) posterior covariance - rather than assuming independent errors across all 8760 h, which would understate uncertainty through unrealistic cancellation - correlated function realisations were drawn jointly on a coarse 22x22 (H_s , T_e) grid using the fitted GP's full posterior covariance, and each hourly sea state was mapped to its nearest grid node before summing to an annual total. The physical-model posterior-predictive AEP distribution (from the MCMC parameter posterior) and the GPR-based AEP distribution provide two independent Bayesian estimates of the same quantity, allowing cross-model validation.

Carbon-Footprint Comparison Framework

Life-cycle carbon intensities (CI, g CO₂-eq kWh⁻¹) were assigned literature-based probability distributions rather than single point values. For the WEC, a truncated-Normal distribution with mean 53 g CO₂-eq kWh⁻¹, standard deviation 29 g CO₂-eq kWh⁻¹, and bounds (15, 105) g CO₂-eq kWh⁻¹ was used, following the cross-technology meta-analysis of ocean-energy life-cycle assessments by Uihlein [1], who also reports an assumed 20% capacity factor for wave devices and notes that point-absorber and rotating-mass devices - the RM3 category - trend toward the upper part of this range. Fossil-fuel comparators used triangular distributions bounded by the minimum, mode (harmonised median) and maximum values reported in the IPCC Fifth Assessment Report's technology-specific cost and performance annex [8]: coal (no carbon capture), 660-820-1050 g CO₂-eq kWh⁻¹; natural gas combined cycle, 410-490-650 g CO₂-eq kWh⁻¹ (cross-checked against the World Nuclear Association's harmonised life-cycle compilation [9]).

A Monte Carlo simulation with 100,000 draws combined: (i) AEP, resampled with replacement from the pooled physical-Bayesian and ML-Bayesian posterior-predictive AEP distributions (an equal-weight Bayesian model average across the two independent modelling approaches), inflated by an additional +/-6% (1 SD) multiplicative factor to represent inter-annual wave-climate variability not captured by the single synthetic year; (ii) the WEC carbon-intensity distribution; and (iii) the coal and gas carbon-intensity distributions. For each draw, annual avoided emissions were computed as

$$\Delta CO_2 = AEP \times (CI_{fossil} - CI_{WEC}) \quad (7)$$

for each fossil comparator, together with the relative emissions-reduction percentage and the cumulative avoided emissions over an assumed 25-year device design life. All posterior and Monte Carlo summaries are reported as the mean, standard deviation, and the 95% credible interval (2.5th-97.5th percentile).

RESULTS

Wave Resource Characterisation

The synthesised hourly sea-state record reproduces the seasonal pattern reported for PacWave South, with H_s ranging from 0.9 m to 7.9 m over the year (annual mean 2.5 m) and T_e ranging from 6.1 s to 13.7 s (annual mean 9.8 s); monthly means spanned 1.75–3.6 m for H_s , closely matching the cited monthly-mean range of 1.75–3.5 m [7] (Figure 1a). The joint (H_s , T_e) distribution (Figure 1b) shows the expected positive correlation between wave height and period, with the most energetic, longer-period sea states concentrated in the winter months.

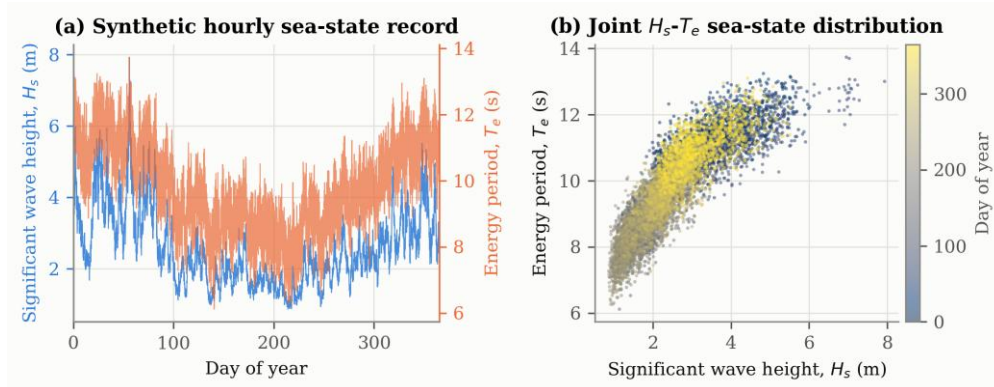


Figure 1. Case-study wave resource: (a) synthetic hourly significant wave height (H_s) and energy period (T_e) time series over a representative year, statistically calibrated to the published PacWave South monthly climatology [7]; (b) joint H_s - T_e distribution, coloured by day of year.

Physical-Model Power Performance

With the characteristic capture width calibrated to a 20% resource-averaged capacity factor ($W = 10.60$ m), the physical model predicts an AEP of 501.1 MWh yr⁻¹ for the 286 kW reference device, with a mean annual wave power flux of 39.4 kW m⁻¹ across the resource series. The resulting power matrix (Figure 2a) shows the expected resonance ridge near $T_e \approx 9.5$ s, with output saturating toward the rated capacity only in the most energetic, and comparatively rare, winter sea states; a representative winter week (Figure 2b) illustrates the resulting short-term variability in simulated electrical output.

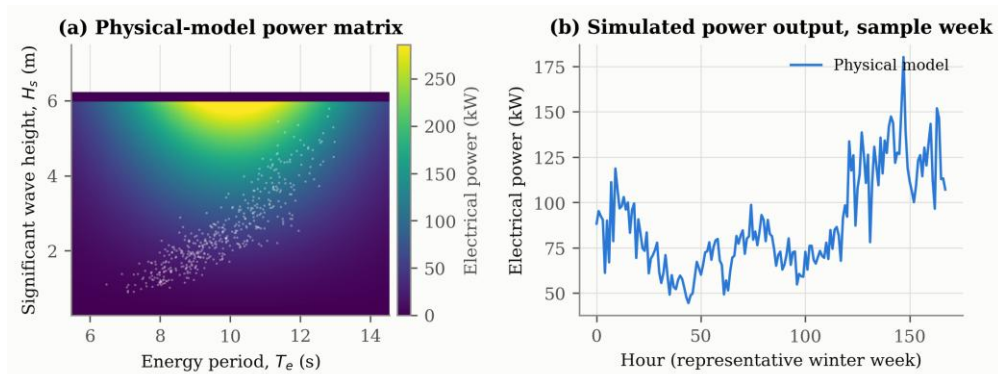


Figure 2. Physical (wave-to-wire) model: (a) power matrix as a function of H_s and T_e , with the annual sea-state record overlaid (white points); (b) simulated electrical power output over a representative winter week.

Machine-Learning Model Validation

Both ML models reproduced the (synthetic) observed power data closely on the held-out test set (Figure 3a). The deterministic GBR benchmark achieved RMSE = 5.48 kW, MAE = 4.00 kW and $R^2 = 0.984$. The Bayesian GPR model achieved RMSE = 13.65 kW, MAE = 4.30 kW and $R^2 = 0.903$, with a mean posterior-predictive standard deviation of 5.07 kW and an empirical 95% predictive-interval coverage of 93.1% on the test set (Table 1), indicating that the GPR's quantified uncertainty is close to nominally well-calibrated. Figure 3b shows the GPR posterior mean and 95% predictive interval tracking the observed power curve across the full range of test sea states, with interval width increasing, as expected, at higher sea states where the assumed measurement noise (and hence predictive uncertainty) is largest.

Table 1. Machine-learning model performance on the held-out test set.

Metric	GBR (point estimate)	GPR (Bayesian)
RMSE (kW)	5.48	13.65
MAE (kW)	4.00	4.30
R^2	0.984	0.903
Mean predictive SD (kW)	-	5.07
95% interval coverage	-	93.1%

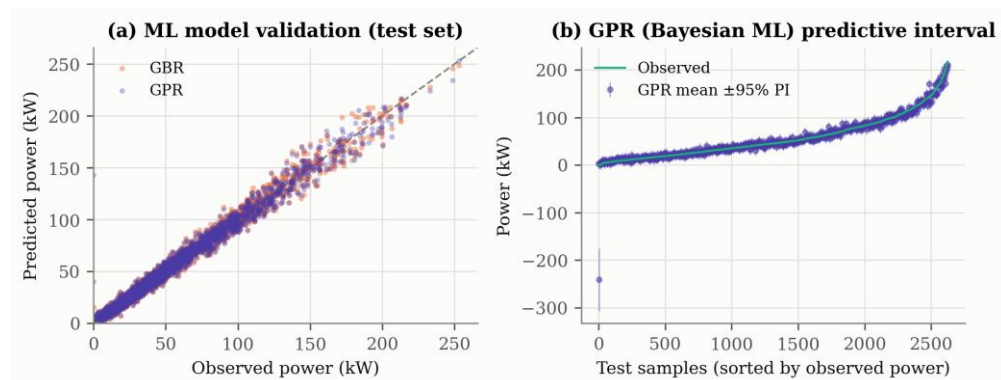


Figure 3. Machine-learning model validation: (a) predicted vs. observed power for the Gradient Boosting (GBR) and Gaussian Process (GPR) models on the held-out test set, with the 1:1 line shown for reference; (b) GPR posterior mean and 95% predictive interval against observed power, test samples sorted by observed power.

Bayesian Calibration of the Physical Model

The four-chain MCMC calibration converged well for all parameters, with Gelman-Rubin R -hat between 1.0009 and 1.0079 (all ≤ 1.01 , the conventional convergence threshold) and effective sample sizes between 598 and 2,693 across 4 chains of 15,000 iterations each (acceptance rates 19.9–20.7%; Figure 4, top row and bottom-left panel). The posterior recovered parameter values close to the data-generating (nominal literature) values used to construct the synthetic observed dataset: $CWR_{max} = 0.2503$ (95% CrI 0.2481–0.2526; true value 0.250), $T_{e0} = 9.475$ s (95% CrI 9.408–9.537; true value 9.5 s), and $\sigma_{Te} = 2.517$ s (95% CrI 2.446–2.593; true value 2.5 s) (Figure 4, bottom-right panel; Table 2), confirming that the MCMC procedure can recover known hydrodynamic parameters from noisy power-performance data. Propagating the full parameter posterior through the

physical model yielded an AEP posterior-predictive mean of 500.8 MWh yr⁻¹ (SD 1.6; 95% CrI 497.6-503.8 MWh yr⁻¹), closely matching the calibration-target physical-model estimate.

Table 2. Bayesian posterior summary for the calibrated hydrodynamic parameters (four chains, 40,000 pooled post-burn-in draws).

Parameter	Prior	Posterior mean (SD)	95% CrI	R- hat	E SS
CWR _{max}	Uniform(0, 15, 0.35)	0.2503 (0.0011)	0.2481- 0.2526	1.0009	2, 693
T _{e0} (s)	Normal(9.5, 1.0)	9.475 (0.033)	9.408- 9.537	1.0013	63 7
σ_{Te} (s)	Normal(2.5, 0.6)	2.517 (0.037)	2.446- 2.593	1.0011	62 3
log(noise scale)	Normal(0, 0.3)	0.013 (0.025)	-0.035- 0.066	1.0079	59 8

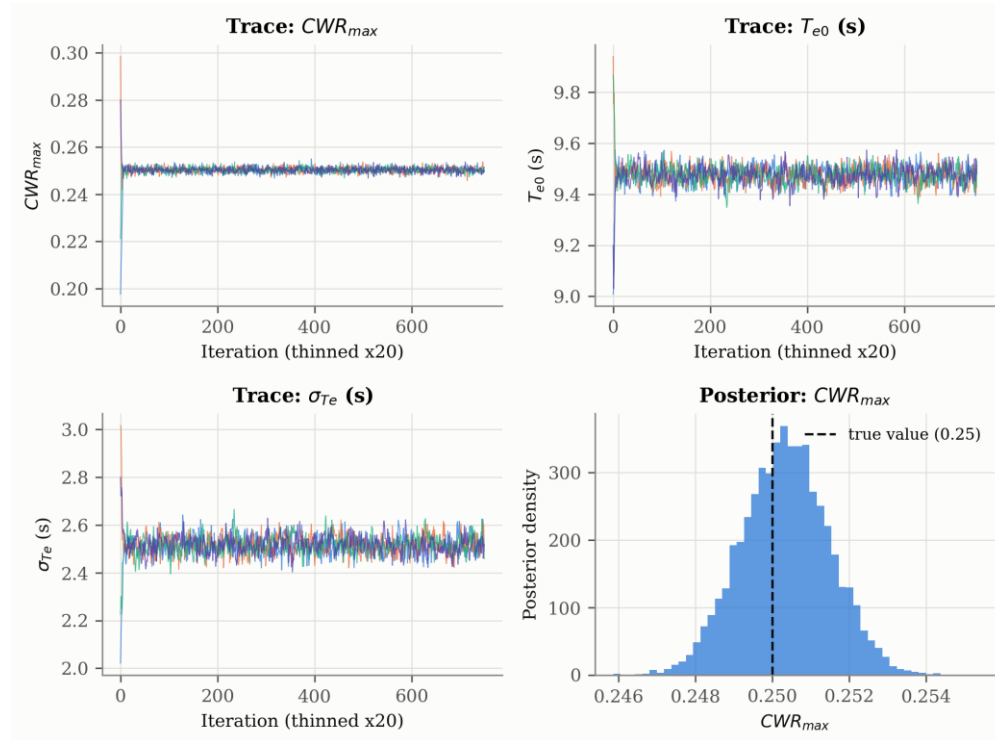


Figure 4. Bayesian MCMC calibration diagnostics: trace plots for CWR_{max}, T_{e0} and σ_{Te} across four independent chains (thinned x20), and the pooled posterior distribution of CWR_{max} against its data-generating value.

Comparative Carbon-Footprint Analysis

The pooled (physical-Bayesian and ML-Bayesian) AEP posterior used for the carbon-footprint propagation had a mean of 477.1 MWh yr⁻¹ (SD 37.4; 95% CrI 407.7-550.0 MWh yr⁻¹) after including the additional inter-annual resource-variability inflation; the two independent models agreed to within 9.4% of one another, providing mutual validation (Figure 5a).

The Monte Carlo simulation (100,000 draws) produced life-cycle carbon-intensity distributions of 56.0 (SD 21.9) g CO₂-eq kWh⁻¹ for the WEC, versus 516.6 g CO₂-eq kWh⁻¹ for natural gas and 843.5 g CO₂-eq kWh⁻¹ for coal (Figure 5b; Table 3), an order-of-magnitude difference. Combined with the AEP posterior, the WEC's own annual life-cycle emissions were estimated at 26.7 t CO₂-eq yr⁻¹ (95% CrI 8.7-47.9), against 246.5 t CO₂-eq yr⁻¹ for an equivalent gas-fired generator and 402.4 t CO₂-eq yr⁻¹ for an equivalent coal-fired generator producing the same energy (Table 4).

Annual avoided emissions were estimated at 375.7 t CO₂-eq yr⁻¹ relative to coal (95% CrI 287.5-479.3; 93.3% relative reduction, 95% CrI 87.8-97.8%) and 219.8 t CO₂-eq yr⁻¹ relative to natural gas (95% CrI 164.7-286.3; 89.1% relative reduction) (Figure 6a). Over an assumed 25-year design life, cumulative avoided emissions reached a posterior median of 9.32 kt CO₂-eq relative to coal (95% CrI 7.19-11.98 kt) and 5.44 kt CO₂-eq relative to natural gas (95% CrI 4.12-7.16 kt) (Figure 6b; Table 4).

Table 3. Life-cycle carbon-intensity assumptions (g CO₂-eq kWh⁻¹) used in the Monte Carlo simulation.

Source	Distribution	Parameters	Reference
WEC (device)	Truncated Normal	$\mu=53$, $\sigma=29$, bounds [15, 105]	[1]
Coal (no CCS)	Triangular	min=660, mode=820, max=1050	[8,9]
Natural gas (CC)	Triangular	min=410, mode=490, max=650	[8,9]

Table 4. Monte Carlo carbon-footprint comparison summary (posterior mean (SD); 95% credible interval).

Quantity	Mean (SD)	95% CrI
AEP (MWh yr ⁻¹)	477.1 (37.4)	407.7-550.0
WEC annual emissions (t CO ₂ -eq yr ⁻¹)	26.7 (10.7)	8.7-47.9
Coal-equivalent emissions (t CO ₂ -eq yr ⁻¹)	402.4 (49.7)	314.0-506.6
Gas-equivalent emissions (t CO ₂ -eq yr ⁻¹)	246.5 (30.7)	192.7-311.9
Avoided vs. coal (t CO ₂ -eq yr ⁻¹)	375.7 (49.5)	287.5-479.3
Avoided vs. gas (t CO ₂ -eq yr ⁻¹)	219.8 (31.3)	164.7-286.3
Relative reduction vs. coal (%)	93.3 (2.7)	87.8-97.8
Relative reduction vs. gas (%)	89.1 (4.4)	80.1-96.5
25-yr cumulative avoided vs. coal (kt CO ₂ -eq)	9.39 (1.24)	7.19-11.98
25-yr cumulative avoided vs. gas (kt CO ₂ -eq)	5.49 (0.78)	4.12-7.16

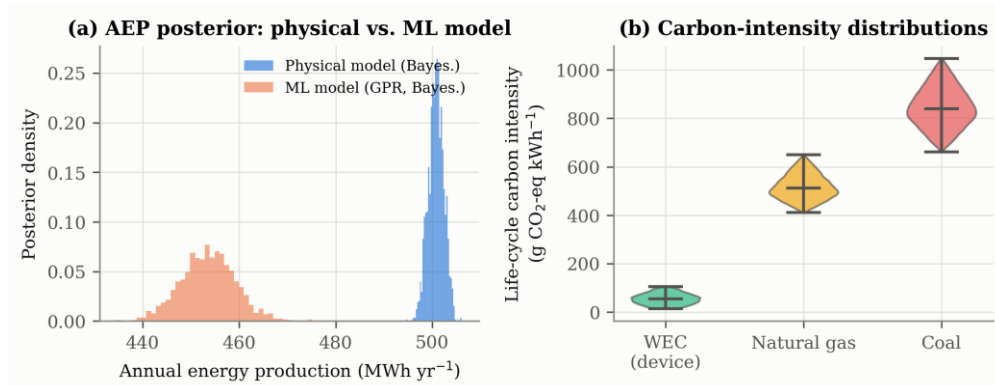


Figure 5. (a) Posterior-predictive AEP distributions from the physical (Bayesian-calibrated) and machine-learning (GPR, Bayesian) models; (b) life-cycle carbon-intensity distributions for the WEC, natural gas, and coal.

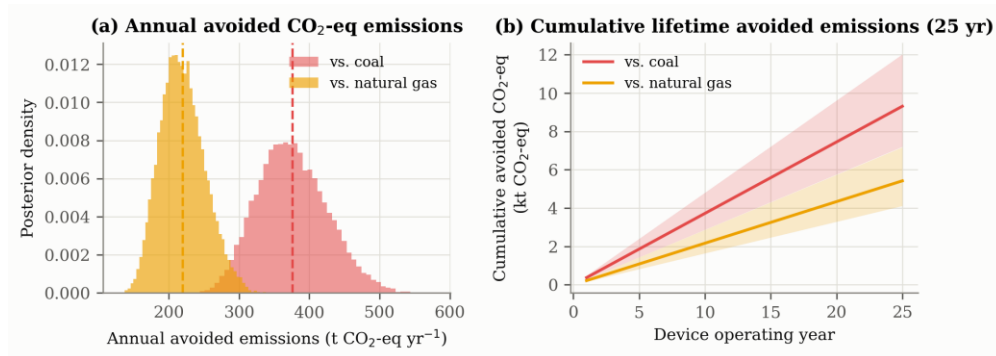


Figure 6. (a) Posterior distribution of annual avoided CO₂-eq emissions relative to coal and natural gas (dashed lines: posterior means); (b) cumulative avoided CO₂-eq emissions over a 25-year device design life (solid line: posterior median; shaded band: 95% credible interval).

DISCUSSION

The close agreement between the physically-calibrated Bayesian model and the independent, data-driven GPR model - AEP estimates within roughly one-tenth of one another, arrived at through entirely different modelling assumptions - provides a useful, low-cost form of model validation that is often absent from single-model resource-to-power assessments. It also illustrates a broader methodological point: a physical model provides interpretable, extrapolable structure (and here, could recover its own known generating parameters from noisy data via MCMC with good convergence), while a Bayesian ML model provides a check that is not conditioned on any particular assumed functional form, at the cost of interpretability and, in this implementation, exact-GP scalability.

The resulting carbon-footprint comparison shows that, even accounting for the wide literature-reported range of ocean-energy life-cycle emissions [1] and for fossil-fuel life-cycle ranges that include upstream methane leakage and fuel-cycle emissions [8,9], a wave energy converter of this class is expected to displace on the order of 90% of the emissions of an equivalent fossil generator, with the 95% credible interval for the relative reduction remaining above 80% against natural gas and above 87% against coal even under the combined effect of AEP, device-LCA and fossil-LCA uncertainty [15-18]. This robustness to compounded uncertainty is itself a policy-relevant finding: the qualitative

decarbonisation case for wave energy at a resource-rich site such as PacWave South does not depend sensitively on any single disputed parameter.

Several limitations should be noted. First, the sea-state record is a single statistically-calibrated representative year rather than a multi-year measured record; while an explicit inter-annual variability inflation was included in the Monte Carlo propagation, it is a simplifying assumption rather than an empirically estimated inter-annual spectrum. Second, the capture-width-ratio model is a parsimonious, single-resonance empirical form calibrated to reproduce a literature-typical capacity factor; it is not a substitute for a full hydrodynamic (e.g., boundary-element or CFD) model of the RM3 geometry, and higher-order effects such as directional spreading, nonlinear wave loading, and active PTO control strategies are not represented. Third, the non-identifiability of CWR_max and η_{PTO} from power-curve data alone required fixing the PTO efficiency at a nominal value; a study with independent drivetrain-efficiency measurements could relax this assumption. Fourth, the carbon-footprint analysis considers only operational-lifetime GHG emissions on a per-kWh life-cycle basis and does not extend to a full comparative life-cycle assessment (e.g., material extraction, decommissioning logistics, ecological effects, or land/seabed-use impacts), nor to other environmental or socio-economic dimensions of marine energy deployment. Finally, the GPR training subsample trades some predictive accuracy for computational tractability; sparse or variational GP methods could relax this constraint in future work at higher implementation complexity.

Notwithstanding these limitations, the framework presented here - physical model, independent Bayesian ML cross-check, formally diagnosed MCMC calibration, and Monte Carlo uncertainty propagation into a decision-relevant carbon-footprint metric - is directly transferable to other marine energy converters and sites, and to other decision-relevant outputs such as levelised cost of energy, provided that appropriate resource data and device-performance priors are available.

CONCLUSION

This study implemented and cross-validated a physical wave-to-wire model and a Bayesian machine-learning (Gaussian Process Regression) model for a reference point-absorber wave energy converter at the PacWave South test site, calibrated the physical model's hydrodynamic parameters via a formally-diagnosed four-chain MCMC procedure, and propagated the resulting posterior-predictive annual-energy-production uncertainty, together with literature-based life-cycle carbon-intensity distributions, through a 100,000-draw Monte Carlo simulation to quantify avoided greenhouse-gas emissions relative to coal- and gas-fired generation. The two independent power models agreed closely (within about one-tenth of one another in mean AEP), and the device was estimated to avoid on the order of 90% of the life-cycle carbon emissions of an equivalent fossil-fuel generator, with credible intervals that remain favourable even under compounded resource, model and life-cycle-assessment uncertainty. The principal advantages of the approach are its transparency (every assumption is an explicit, cited prior or literature value), its internal cross-validation (physical vs. ML model agreement), and its direct translation of technical uncertainty into decision-relevant, credible-interval carbon-footprint estimates. Its main limitations are its reliance on a statistically-calibrated synthetic (rather than raw measured) resource record, a simplified single-resonance capture-width model, and a scope restricted to operational-phase carbon intensity rather than full life-cycle assessment. The framework is directly applicable to other wave, tidal,

and marine current energy converters and sites, and offers a template for uncertainty-aware, evidence-based appraisal of marine renewable energy's contribution to decarbonisation.

ACKNOWLEDGMENT

The authors gratefully acknowledge the public availability of the resource-characterisation and reference-device datasets compiled under the U.S. Department of Energy's Water Power Technologies Office programmes (PacWave and the Reference Model Project), which made this case study possible.

CONFLICT OF INTERESTS

The authors declare that there is no conflict of interest associated with this publication.

DATA AVAILABILITY

The hourly sea-state record used in this study is a statistically-calibrated synthetic series (not raw measured buoy data) constructed to reproduce the monthly wave-climate statistics publicly reported for the PacWave South test site [7]; the generation procedure is fully described in research and implemented in the accompanying Python code. All model code (physical model, machine-learning model, MCMC sampler, and Monte Carlo carbon-footprint propagation), together with the numerical results and figures underlying this manuscript, are provided as Supplementary Material to support full reproducibility.

NOMENCLATURE

Symbol	Definition (unit)
H_s	Significant wave height (m)
T_e	Wave energy period (s)
J	Deep-water omnidirectional wave power flux (kW m^{-1})
ρ	Seawater density, 1025 kg m^{-3}
g	Gravitational acceleration, 9.80665 m s^{-2}
CWR	Capture-width ratio (dimensionless)
CWR_{max}	Peak capture-width ratio
T_{e0}	Resonant (most efficient) energy period (s)
σ_{Te}	Bandwidth of the capture-width resonance response (s)
W	Characteristic capture width (m)
η_{PTO}	Power take-off (drivetrain/generator) efficiency
P_{rated}	Nameplate rated electrical power (kW)
AEP	Annual energy production (MWh yr^{-1})
CF	Capacity factor (dimensionless)
CI	Life-cycle carbon intensity ($\text{g CO}_2\text{-eq kWh}^{-1}$)
θ	Vector of calibrated physical-model parameters

$R'(R\text{-hat})$

Gelman-Rubin potential scale reduction factor

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