

Wave extremes diverge from mean conditions under climate change

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Wave extremes diverge from mean conditions under climate change

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Ocean wave extremes drive major coastal hazards, yet whether they evolve consistently with mean conditions under climate change remains unclear. Here, we present a global assessment of projected changes in wave height extremes based on a large CMIP6 multi-model ensemble, combining complementary extreme-value and exceedance-based approaches within a structured uncertainty framework. We find consistent increases in extreme wave heights across the mid-latitudes of the North Pacific, North Atlantic and Southern Ocean. In the North Atlantic and North Pacific, however, such increases occur despite projected decreases in mean conditions, demonstrating that changes in extremes cannot be reliably inferred from the changes in the means. Coastal indicators reveal sensitivity to projected wave climate changes along more than 60% of the global coastline. Together, our results show that wave extremes exhibit coherent large-scale changes that can diverge from changes in mean conditions, highlighting the need for dedicated assessments of future coastal hazards based on extremes.

Projected changes in ocean wind-wave climate are often inferred from mean conditions, yet whether wave extremes evolve consistently with mean conditions remains unclear. This uncertainty is critical for anticipating wave-driven hazards and supporting adaptation in vulnerable coastal regions, where impacts such as flooding¹⁻⁵, erosion⁶⁻⁸ and infrastructure failure^{9,10} are often governed by extreme wave events.

In this context, identifying where wave extremes intensify is therefore essential, particularly in regions with growing coastal populations and increasing concentrations of assets in low-lying areas¹¹⁻¹⁴, where enhanced extremes may further compound risks associated with sea level rise (SLR)¹⁵⁻¹⁷ and increased storminess¹⁸⁻²⁰. Determining whether wave extremes diverge from mean conditions is equally critical, as it directly affects how future wave hazards are interpreted, quantified, and incorporated into adaptation planning. Nevertheless, global wave climate assessments remain less mature than those of other core variables such as temperature, precipitation, and mean sea level²¹, despite sea state being considered an Essential Climate Variable by the Global Climate Observing System (GCOS)²². This gap arises because waves are not explicitly resolved in most General Circulation Models (GCMs), requiring dedicated

spectral wave models (or related surrogate models^{23–25}) to generate wave climate projections, primarily forced by GCM surface winds and sea-ice concentration.

Wave climate studies have evolved alongside different phases of the Coupled Model Intercomparison Project (CMIP). However, most studies have relied on relatively small and independent ensembles^{24,26–47}, limiting uncertainty quantification across scenarios, GCM forcings, and wave modeling approaches. To address these limitations, the Coordinated Ocean Wave Climate Project (COWCLIP) provides a community-based framework for the generation and intercomparison of wave climate projections, enabling consistent global assessments and improved quantification of uncertainties. This international coordinated effort has contributed substantially to the evidence base assessed in Intergovernmental Panel on Climate Change (IPCC) reports. Building on previous CMIP-based efforts (COWCLIP-1, based on CMIP3²⁶, and COWCLIP-2, based on CMIP5^{48,49}), a new COWCLIP-3 ensemble has been developed from CMIP6 simulations, comprising 30 wave model realizations from 15 CMIP6 GCMs across multiple future scenarios (SSP1–2.6, SSP2–4.5 and SSP5–8.5; see [Methods](#)).

Although changes in mean wave conditions have been relatively well documented, the response of wave extremes to climate change remains substantially less understood. Existing assessments are limited in number, based on small ensembles, often regionally inconsistent and/or mostly focused on high-frequency extremes^{50–54}. Consequently, a systematic global assessment of projected changes in wave extremes, including their convergence with or divergence from mean conditions, remains lacking.

Here, we use COWCLIP-3 to assess projected changes in global mean and extreme wave climates, with a primary focus on extreme wave heights and their relationship to mean conditions, including potential divergences. Changes in extremes are evaluated using complementary approaches that characterize extremes across a broad range of exceedance probabilities to provide a robust and comprehensive assessment, according to the IPCC uncertainty framework²¹.

Projected changes in mean wave climate

The ensemble was evaluated against the ERA5⁵⁵ wave reanalysis (ensemble in [Figure 1](#) and [Figure SM2](#); individual members in [Figure SM3–8](#)) and satellite altimetry wave observations⁵⁶ ([Figure SM1](#)), showing modest biases in magnitude and variability across the global ocean, supporting the assessment of projected changes (more details in [Supplementary Material](#)). We first examine changes in mean wave climatologies, including wave height, period, direction and energy flux, represented by significant wave height (H_s), peak wave period (T_p), mean wave direction (Dir_m) and wave energy flux (C_gE), respectively (see [Methods](#) for definitions). These mean-state changes provide a background against which changes in extremes are subsequently evaluated, with [Figure 2](#) contrasting the low and very high GHG-emissions scenarios (SSP1–2.6 and SSP5–8.5, respectively) and the intermediate SSP2–4.5 scenario shown in [Figure SM9](#).

Projected changes in mean H_s exhibit a global pattern across scenarios and time horizons that is broadly consistent with CMIP5-based assessments⁴⁸. Widespread decreases dominate the Northern Hemisphere (NH) mid-latitudes, where they are *likely to very likely* (see [Methods](#)) by end-of-century under SSP5–8.5. These decreases are consistent with a poleward shift in NH extratropical storm tracks^{57–60}, together with a weakening of mid-latitude surface winds⁶¹ and an increase in blocking patterns⁶². In contrast, a latitudinal pattern emerges in the Southern Hemisphere (SH) mid-latitudes, with decreases (increases) north (south) of $\sim 45^\circ\text{S}$, consistent with a poleward shift of the SH extratropical storm tracks⁶³, linked to a positive trend of the Southern Annular Mode and a strengthening of the westerlies^{64,65}. South of 45°S (Southern Ocean; SO), H_s increases become *very likely* across most regions by end-century under SSP5–

8.5 (Figure 2q). Tropical regions display weaker and more heterogeneous responses, with decreases dominating most basins, generally *likely to very likely* under SSP5–8.5. Conversely, localized increases emerge in the southeastern Pacific (*likely* under SSP5–8.5 by end-century), consistent with enhanced SO swell energy and intensified southeasterly trade winds^{26,39,50}. Additional increases are also identified at the northernmost Indian latitudes (*very likely* under SSP5–8.5 by end-of-century).

Projected changes in mean C_gE largely mirror those of H_s, albeit with generally greater relative magnitudes. The increasing signal in the eastern tropical Pacific extends latitudinally, becoming *very likely* under SSP5–8.5 by end-century. The North Atlantic shows decreases across most of the basin under SSP5–8.5 by end-century, whereas the SO exhibits *very likely* increases by end-of-century. The Indian Ocean maintains a general decrease characterized by high uncertainty.

Mean T_p shows a widespread projected increase (*likely to very likely*) across most of the SH, consistent with increasing swell energy from the SO, with the tropical southwestern Pacific as the main exception. In contrast, the NH exhibits more heterogeneous responses, with decreases projected in the western Pacific sector and the North Atlantic under SSP5–8.5, and increases in the eastern Pacific sector (*likely to very likely*). In the Indian Ocean, increases are widespread (*likely to very likely*), except in its westernmost sector, where decreases are *likely*.

Changes in Dir_m exhibit coherent large-scale rotational patterns, predominantly clockwise across tropical latitudes and anticlockwise in the SH mid-latitudes, consistent with CMIP5-based results⁴⁸. Tropical regions show *likely* (*likely to very likely*) clockwise changes in the Pacific and Atlantic by mid-century (end-of-century) under SSP5–8.5. In contrast, anticlockwise rotations in the SH mid-latitudes are *likely to very likely* under SSP5–8.5 across the Indian, Atlantic and eastern Pacific sectors, consistent with the poleward shift of SO wave generation areas⁶⁶. In the NH mid-latitudes, responses are more heterogeneous, with clockwise rotations dominating the Atlantic (*likely to very likely* between 30°N and 45°N), while anticlockwise rotations emerge in the eastern Pacific sector (*likely to very likely*).

Projected changes in wave extremes

Against this background, we next examine wave extremes, assessed through extreme H_s, which largely determine the most consequential manifestations of a changing wave climate, and assess whether their projected changes are consistent with, or diverge from, the underlying mean conditions. We evaluate these changes using two complementary approaches: return levels and non-parametric metrics to characterize the frequency and magnitude of threshold exceedances. Together, these approaches provide a consistent assessment across a broad range of extreme-event probabilities.

We first analyze threshold exceedances above a fixed historical threshold (99th percentile of H_s; see [Methods](#)), quantifying projected changes in both their frequency and mean magnitude ([Figure 3](#); SSP2–4.5 in [Figure SM11](#)). Changes in the exceedance occurrence exhibit relatively low uncertainty and largely follow the spatial patterns observed in high percentile H_s ([Figure SM10](#)). This indicates that changes in occurrence are strongly influenced by shifts in the mean wave climate. Widespread decreases in frequency dominate the NH, particularly in the North Atlantic (*high confidence*), with a ~60% reduction in tropical regions by end-century under SSP5–8.5, and in the tropical North Pacific (*medium to high confidence*). In contrast, increases are observed in the southeastern tropical Pacific and the SO, with *high confidence* under SSP5–8.5 by end-century, and *medium to high confidence* otherwise. The Indian Ocean shows a generalized decrease, with *high confidence* (*low to medium confidence*) in the northern (southern) regions under SSP5–8.5.

In contrast to the changes in frequency, projected changes in exceedance magnitude are spatially noisier and more uncertain, particularly in tropical latitudes (Figure 3). However, they exhibit clear differences relative to changes in frequency, particularly for the NH. Increasing magnitudes are identified in the North Pacific and the North Atlantic (*medium to high confidence*), with higher confidence for mid-century under both scenarios. This indicates that exceedances above the historical threshold become more severe despite a generalized decrease in the mean H_s . Increases are also projected across the SO, with *high confidence* under SSP5–8.5 by end-century. The western Arabian Sea also shows increasing magnitudes (*high confidence*), except for SSP1–2.6 by end-century.

We next examine low-frequency wave extremes, defined here as H_s events associated with return periods ranging from 10 to 50 years (50-year return levels in Figure 4 and Figure SM12; 10- and 25-year return levels in Figure SM13). Return levels are estimated using a non-stationary extreme-value analysis of monthly maxima of H_s (see Methods). This approach characterizes both intensity and occurrence of low-frequency events, allowing projected changes to be assessed in terms of return levels and associated return periods.

Projected changes reveal a coherent large-scale intensification of low-frequency extremes across the mid-latitudes, with consistent signals across scenarios and time horizons, although confidence is lower under SSP1–2.6. The projected intensification is most pronounced during the winter season in each hemisphere (Figure SM14). Across NH mid-latitudes, increases extend poleward to ~55°N in the Pacific, being mainly concentrated between 35° and 50° in the Atlantic. Under SSP5–8.5 by end-century, return levels locally exceed 5% increases in the western and eastern North Atlantic sectors, corresponding to a shortening of historical 50-year return periods to 20–40 years (*medium confidence*), with comparable signals in the North Pacific. Increases are also projected by mid-century under SSP1–2.6 in both basins, with *medium to high confidence* in several regions. Prevailing increases are also projected in the SH mid-latitudes, widely assessed with *medium to high confidence*, locally reaching ~10%. In some areas, the historical 50-year H_s is projected to recur in less than 10 years by the end of the century under SSP5–8.5.

In contrast, tropical regions exhibit more heterogeneous responses, generally dominated by decreases and limited inter-model agreement. Exceptions are the equatorial Pacific, where increases are projected consistently across scenarios, with *medium to high confidence* under SSP5–8.5 by end-century, and the East China Sea, with *medium confidence* under the same scenario. Consistent increases are also identified in the Arabian Sea, with *high confidence* under SSP5–8.5 by end-century and *medium confidence* otherwise. Elsewhere, projected decreases across the tropical Atlantic, Pacific, and Indian basins are typically characterized by *low confidence*. Regional exceptions include the western tropical Atlantic, northwestern tropical Pacific, and southeastern tropical Pacific under SSP5–8.5 by end-century (*medium to high confidence*), where future return periods associated to historical 50-year return levels locally exceed 100 years.

Wave extremes in several tropical regions are strongly driven by tropical cyclones (TCs), with their regions of influence shown in Figure SM15. Their indirect influence can extend poleward as a result of many TC transitioning to post-tropical cyclones, particularly in the North Atlantic⁶⁷. Here, no explicit separation between TC-induced extremes and other wave systems is performed. Although the non-stationary EVA can implicitly capture TC contributions, results in TC-dominated regions should be interpreted with caution, given the known underestimation⁶⁸ of TC frequency and intensity in GCMs and their substantial inter-model differences⁵⁰ (Figure SM16). The GEV framework may also reflect differences in the statistical behavior of extremes across wave-generation regimes through its shape parameter, which has previously been associated with tropical-cyclone- and extratropical-storm-dominated environments^{50,53}.

Confidence estimates may therefore be locally overestimated. While studies based on synthetic TC generation provide a more targeted framework to assess changes in TC-driven extremes^{68,69}, direct comparability with our analysis is constrained, as tropical extremes may have different origins. However, comparisons still indicate broadly consistent signs and spatial patterns of changes in TC-affected regions, although uncertainty estimates differ. This underscores the need for integrated approaches that explicitly account for multiple wave-generation mechanisms, including TCs.

Both approaches provide a consistent picture of changes in the tail of the H_s distribution: the mean magnitude of threshold exceedances provides an integrated characterization of the upper tail of the distribution, whereas return levels from 10 to 50 years characterize low-probability extremes within the upper tail. Their convergence indicates coherent responses across a broad range of extreme-event probabilities despite characterizing extremes through fundamentally different methodological frameworks (empirical and theoretical).

Results consistently indicate increasing wave extremes across the mid-latitudes of the North Pacific and North Atlantic under both low- and high-emission scenarios, with the clearest signals occurring during boreal winter. While increases in the North Pacific have been reported previously, often with substantial uncertainty^{50,51}, North Atlantic mid-latitude changes have been variable. Previous studies reported highly uncertain and spatially noisy patterns in this region under end-century high-emission scenarios, commonly attributed to uncertainties in the representation of North Atlantic storm tracks⁷⁰. Here, both approaches reveal consistent increases, based on an ensemble substantially larger than in previous studies. This has direct implications for risk assessment in highly populated coastal regions of the North Atlantic and North Pacific. Our results are consistent with the projected poleward shift, contraction and intensification of NH storm tracks during boreal winter^{57,71,72}, and particularly with the increasing frequency of extreme extratropical cyclones⁵⁸. Additionally, enhanced intensity and poleward expansion of tropical and post-tropical cyclones under climate change may contribute further⁷³.

The two approaches also concur in projecting increases in wave extremes across the SO, consistent with earlier CMIP5-based assessments^{50,51}, similarly showing a reduction in uncertainty under high emissions toward the end of the century. This pattern aligns with the poleward shift and intensification of the SH storm track during austral winter, together with the increase in extreme cyclones^{58,74,75}. In the western Arabian Sea, increases show strong inter-model agreement across all periods and scenarios, consistent with an intensification and northward shift of the Somali Jet^{76,77}. Additional regions of agreement include the eastern tropical South Indian Ocean, particularly under high emissions by end-century, and the equatorial eastern Pacific, with clear increases across periods and scenarios, and lower uncertainty than reported previously^{50,51}, despite consistent signs of change. These patterns align with the strong intensification of SO wave extremes. Conversely, a marked disagreement emerges for the South Atlantic: while earlier studies suggested increasing extremes, often with high inter-model agreement⁵¹, our ensemble reveals a response dominated by decreases under both approaches, hindered by substantial uncertainty. Overall, consistent large-scale changes in wave extremes can be identified despite regional uncertainties, particularly across mid-latitudes, where both approaches converge.

Consistency between mean and extreme wave changes

Having assessed changes in mean wave conditions and extremes separately, we integrate these results to identify regions of agreement and divergence. These contrasts imply that changes in the upper tail of the H_s distribution do not necessarily mirror those in mean conditions. **Figure 5** combines projected changes in mean H_s with those in 50-year return period H_s . Approximately

50–60% of the global ocean exhibits agreement in the sign of change across the four future period-scenario combinations analyzed (Figure 5; SSP2–4.5 in Figure SM17). Such agreement is maximized by end-century under SSP5–8.5, with *moderate* and *high* agreement (see Methods) covering ~40% and ~12% of the global ocean, respectively, versus <26% and <6% otherwise. Consistent increases are observed in the southern mid-latitudes and the eastern tropical Pacific, as evidenced by the analysis of the ensemble-mean H_s distributions (Figure SM18). In contrast, consistent decreases are observed in the central and western tropical Pacific, particularly for end-century under SSP5–8.5.

Several key regions display clear and physically meaningful divergences, nonetheless. Across the mid-latitude North Pacific and broad sectors of the North Atlantic, mean H_s decreases while extremes intensify (Figure SM18).

The assessment of threshold exceedances (Figure 3) provides further insight into this divergence. The North Atlantic exhibits increasing magnitudes alongside decreasing occurrence, suggesting longer quiescent periods punctuated by enhanced extremes. Distributions indicate that mean ensemble divergences occur above the 99th percentile threshold, such that threshold exceedances metrics still partly reflect projected decreases, reducing the coherence of magnitude changes. This is consistent with a clearer increasing signal for higher return periods (Figure 4, Figure SM13). In the North Pacific, by contrast, as the transition occurs below the historical 99th percentile, the mean magnitude of threshold exceedances directly captures the regime of increasing extremes, leading to a more robust intensification signal in both approaches. Exceedance counts become, nevertheless, highly sensitive to small distributional shifts.

With the exception of end-century under SSP1–2.6, these regions exhibit *moderate* to *high* inter-model agreement in this divergent response, extending into the tropical North Pacific by mid-century under both scenarios. These regions are particularly noteworthy, as earlier assessments recurrently identified the North Pacific and the North Atlantic as regions of decreasing mean H_s , often interpreted as indicative of a generalized weakening of wave conditions. The identification of increasing extremes, supported by two complementary approaches and substantial inter-model agreement, highlights a fundamental limitation in inferring extreme behavior from changes in mean conditions.

Similar behavior (*high* agreement) is identified in the eastern Arabian Sea, the East China Sea and across the 30°S–45°S band of the Indian Ocean (ensemble-mean distributions in Figure SM18). Regions where extremes decrease despite increasing mean conditions are less common, occurring locally in the eastern tropical Pacific near 30°S, across scenarios, and in the Gulf of Guinea by mid-century under SSP1–2.6.

Coastal implications

These results have direct implications beyond the open ocean, as potential increases in coastal hazards may occur without an obvious signature in mean conditions. Therefore, extrapolating changes in mean wave climate to infer future extreme behavior may lead to inadequate decision-making, systematically underestimating future hazards in several regions, as changes in the upper tail can diverge from those in the bulk of the distribution.

To evaluate potential consequences of a changing wave climate, we assess how projected offshore changes translate into impact-relevant coastal responses. Although our results lack sufficient resolution for local-scale coastal assessments, they provide a first-order, global-scale indication of how future wave climate changes may affect coastlines. The selected indicators should not be interpreted as direct projections of future impacts, but rather as measures of

coastal sensitivity to projected changes in wave climate. The actual occurrence and magnitude of these impacts also depend on additional factors, including tides, storm surges, SLR, local morphological characteristics, and the type and exposure of coastal environments and assets, which are not represented in our analysis.

Within these limitations, we identify coastal regions particularly sensitive to changes in wave climate using simple, physically-based indicators (see [Methods](#)). We consider three coastal impacts: longshore erosion, storm-related flooding, and damage to coastal protection infrastructure. These are linked to changes in wave direction and energy flux, threshold-exceedance H_s magnitude and 95th percentile T_p , and low-frequency wave extremes, respectively. [Figure 6](#) highlights coastal regions where a potential enhancement of wave-driven impacts is projected, also identifying the underlying specific wave-related drivers.

Projected changes reveal wave-climate sensitivity (see [Methods](#)) along ~62% of the global coastline, including 55% related to erosion, 31% to flooding, and 3% to infrastructure safety, with strong regional contrasts; these categories are non-exclusive and may overlap across coastal segments.

Western continental margins show wave-climate sensitivity to both erosion and flooding. The widespread increases in high-percentile T_p along these regions ([Figure SM10](#)) contribute to the enhanced sensitivity to flooding, whereas Dir_m changes explain the prominence of erosion-related signals. Along the eastern margins of continents sensitivity is mostly dominated by erosion-related indicators, mainly associated with changes in Dir_m .

Flooding-related wave climate sensitivity hotspots are primarily concentrated along tropical Pacific and Atlantic coasts, as well as parts of the Indian Ocean and southern mid-latitudes. These regions may be particularly vulnerable to compound flooding from wave-driven contributions with SLR, particularly along parts of the African coastline where above-average SLR rates have been projected²¹. Erosion-related wave-climate sensitivity hotspots are mainly located along southwestern Africa, the South and Central American coasts, the northern Arabian Sea, and parts of the southern mid-latitudes. Many coincide with previously identified historical hotspots of coastal erosion and accretion^{78,79}, while several are also projected to experience substantial shoreline retreat due to SLR⁸⁰, suggesting the potential for compounded impacts.

Wave climate sensitivity related to coastal protection infrastructure is more spatially fragmented, occurring across parts of the Arabian Sea, Gulf of Alaska, Northern Europe, and selected regions of the Pacific and southern mid-latitudes. These regions host port infrastructures exposed to open-ocean waves^{81,82}, suggesting a potential increase in safety-related risks associated with reduced design lifetimes.

These findings have direct implications for climate-related decision-making. Coastal impact and risk assessments have traditionally focused on SLR, often neglecting projected wave climate changes. Our results show that different coastal impacts, linked to distinct parts of the wave distribution, require dedicated assessments of their respective changes. Accounting explicitly for these differences is essential for more reliable future risk assessments, highlighting the need for dedicated analyses of wave extremes based on large, coordinated ensembles that explicitly quantify uncertainty.

Further advances in wave climate research remain essential to better understand the response of wave conditions to climate change. Improved representation of extremes, including those associated with TCs, remains a key priority, alongside explicit inclusion of ocean waves in GCMs, and higher coastal resolution to better inform impact assessments. Progress along these lines, together with coordinated community ensembles and explicit probabilistic uncertainty

frameworks⁸³, will be critical to translating climate-scale wave projections into actionable information for coastal adaptation.

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Competing interest

The authors declare no competing interests.

Methods

Wave climate projections ensemble

The wave climate projections considered in this study correspond to a subset of the new COWCLIP-3 ensemble, developed within the COWCLIP community, and derived from CMIP6 GCM simulations. The selected ensemble members were produced by eight institutions: Centre for Climate Research Singapore (CCRS), Environment and Climate Change Canada (ECCC), IHCantabria (IHC), Instituto Dom Luiz (IDL), Indian National Centre for Ocean Information Services (INCOIS), Mercator Ocean International (MOI), the National Oceanography Centre (NOC), and CSIRO and the University of Melbourne (CSIRO-UoM).

The ensemble covers SSP1–2.6, SSP2–4.5, and SSP5–8.5, selected to span low, intermediate, and very high forcing levels and thereby characterize both scenario dependence and high-end wave-climate responses. We defined 30-year reference and horizon periods to ensure robust climatological estimates. Changes were evaluated over 30-year periods for mid-century (2036–2065) and end-of-century (2071–2100), relative to the 1985–2014 reference period. The exception was the product from ECCC, providing 20-year coverage for the reference (1995–2014) and future periods (2041–2060 and 2081–2100). Owing to this temporal inconsistency, this member was only considered for changes in mean-based climatological metrics.

The variables considered in this study were the significant wave height (H_s), peak wave period (T_p), wave energy flux (C_gE), and mean wave direction (Dir_m). H_s is defined as the average height of the highest one-third of waves; T_p as the period associated with the maximum spectral energy density; C_gE as the rate of wave energy transport per unit crest length; and Dir_m as the mean direction of wave propagation. The ensemble provides consistent global ocean coverage at a spatial resolution of 0.75° , and all metrics were computed from 3-hourly outputs.

A detailed description of all horizon-scenario-variable combinations included in the analysis is provided in **Table SM1** of the **Supplementary Material**. Although some institutional

contributions have been accompanied by their own performance assessments^{41,42,45,47}, this study conducted a unified evaluation of the performance of all products used, as described below.

Bias assessment

We performed a bias assessment using ERA5 reanalysis and satellite altimetry as reference datasets. ERA5⁸⁴ wave fields (ECMWF/WAM with altimeter assimilation) were used across the 1985–2014 period, with altimetric observations taken from the ESA CCI Sea State v4 Level 4 product⁵⁶, spanning 1995–2014. We computed biases for the mean H_s , and we additionally evaluated the 95th percentile H_s (H_{s95}) from ERA5 only.

We assessed climate-variability representation over 1985–2014 using ERA5 as reference. Two time scales were assessed: (i) intra-annual variability, evaluated as the standard deviation of monthly means normalized by their mean; and (ii) inter-annual variability, evaluated analogously using annual means normalized by their climatological mean⁶².

Extreme-value modelling

We used two complementary approaches to assess projected changes in extreme H_s . The first approach consisted of an empirical assessment of exceedances above a fixed threshold. The second, based on extreme value theory (EVT), was used to evaluate changes in lower frequency extremes.

We assessed changes in both the frequency and magnitude of exceedances above a common threshold applied to the historical and future periods. The threshold was defined as the historical 99th percentile of H_s , which provided adaptive behavior across regions and avoided a fixed global threshold that would correspond to different distributional positions. We extracted exceedances using a peaks-over-threshold (POT) method with a two-day independence period^{51,85,86}. Changes in frequency were computed as the relative difference in mean annual exceedance counts between the future and reference periods, while we computed changes in magnitude as the relative difference in the average intensity of the H_s exceeding the selected threshold.

We assessed low-frequency extremes as events occurring, on average, once every 10, 25 and 50 years. To do so, we fitted monthly maxima of H_s to a seasonally varying, non-stationary generalized extreme value (GEV) model by maximum likelihood estimation^{87–89}. Monthly maxima were used to increase the number of available extreme observations while explicitly accounting for the seasonal cycle of extremes. In the final model formulation, both the location and scale parameters were allowed to vary seasonally, while the shape parameter was estimated independently at each grid cell and kept constant over time. Model complexity was selected independently at each ocean grid point using a forward likelihood-ratio testing approach. We first considered a stationary baseline model (model 0), in which both the location and scale parameters were constant throughout the year. We then compared this baseline against progressively more complex formulations in which the location parameter included annual and, when statistically justified, semi-annual harmonic components (Eq. 1). Starting from the selected location model, we further tested whether adding annual and semi-annual harmonic components to the scale parameter improved the fit (Eq. 2). Additional terms were retained only when they resulted in a statistically significant improvement according to the likelihood-ratio test. This forward selection strategy allowed the model to adapt spatially to different seasonal structures while avoiding unnecessary overparameterization. We then estimated return levels for the historical and future periods (Eq. 3-8).

$$\mu(t) = \beta_0 + \sum_{i=1}^2 \beta_{2i-1} \cos(2i\pi t) + \beta_{2i} \sin(2i\pi t) \quad \text{Eq. 1}$$

$$\log \sigma(t) = \delta_0 + \sum_{i=1}^2 \delta_{2i-1} \cos(2i\pi t) + \delta_{2i} \sin(2i\pi t) \quad \text{Eq. 2}$$

where $t \in [0, 1]$ denotes time within the year, $\mu(t)$ is the time-dependent location parameter, $\sigma(t)$ is the time-dependent scale parameter, and β_i and δ_i are the harmonic coefficients. In the stationary baseline model, all harmonic coefficients are set to zero, so that $\mu(t) = \beta_0$ and $\sigma(t) = \exp(\delta_0)$.

Let $Z(t)$ denote the monthly maximum of H_s occurring at time $t \in [0, 1]$ within the year. The distribution of $Z(t)$ is assumed to follow a GEV location parameter $\mu(t)$, scale parameter $\sigma(t)$, and shape parameter ξ .

For a given threshold z , the conditional non-exceedance probability at time t is:

$$P(Z(t) \leq z) = \exp \left[- \left(1 + \xi \frac{z - \mu(t)}{\sigma(t)} \right)^{-1/\xi} \right], \quad 1 + \xi \frac{z - \mu(t)}{\sigma(t)} > 0. \quad \text{Eq. 3}$$

Assuming independence between monthly maxima, the annual non-exceedance probability of the level z is

$$P_{ann}(Z \leq z) = \exp \left[-12 \int_0^1 \left(1 + \xi \frac{z - \mu(t)}{\sigma(t)} \right)^{-1/\xi} dt \right]. \quad \text{Eq. 4}$$

The integrated return level z_T associated with a return period of T years is defined as the level such that

$$P_{ann}(Z \leq z_T) = 1 - \frac{1}{T}, \quad \text{Eq. 5}$$

which leads to

$$12 \int_0^1 \left(1 + \xi \frac{z_T - \mu(t)}{\sigma(t)} \right)^{-1/\xi} dt = -\ln \left(1 - \frac{1}{T} \right). \quad \text{Eq. 6}$$

Changes in low frequency extremes were assessed in two complementary ways:

- (i) as relative differences in H_s return levels; and
- (ii) by determining the future return period associated with a historical return-level magnitude, by interpolating within the future return level curve.

For seasonal return levels, the fitted non-stationary GEV model was integrated over the months belonging to each climatological season rather than over the full annual cycle. Thus, for a given season S comprising m_S months, the seasonal non-exceedance probability of a level z was defined as

$$P_S(Z \leq z) = \exp \left[- \int_{t \in S} \left(1 + \xi \frac{z - \mu(t)}{\sigma(t)} \right)^{-1/\xi} dN(t) \right], \quad \text{Eq. 7}$$

where $dN(t)$ denotes the monthly occurrence rate within the selected season. In practice, this corresponds to numerically integrating the fitted seasonal cycle over the fraction of the annual cycle associated with each climatological season, so that the integrated seasonal return level $z_{T,S}$ associated with a return period of T years satisfies

$$\int_{t \in S} \left(1 + \xi \frac{z_{T,S} - \mu(t)}{\sigma(t)} \right)^{-1/\xi} dN(t) = -\ln \left(1 - \frac{1}{T} \right). \quad \text{Eq. 8}$$

Accordingly, boreal winter return levels were obtained from December-January-February monthly maxima, spring from March-April-May, summer from June-July-August, and autumn from September-October-November. This approach preserves the seasonal structure of the fitted non-stationary model while providing season-specific extreme-wave estimates directly comparable across historical and future periods.

For the non-stationary GEV models, goodness-of-fit was evaluated using conditional probability-integral-transform (PIT) diagnostics. For each monthly maximum x_i , we computed $u_i = F_{GEV}(x_i; \hat{\mu}(t_i), \hat{\sigma}(t_i), \hat{\xi})$. Under correct model specification, and assuming independence between monthly maxima, the transformed values are expected to follow a *Uniform (0,1)* distribution. Departures from uniformity were summarized spatially using the Kolmogorov-Smirnov discrepancy statistic D , with lower values indicating closer agreement between the fitted model and the observed maxima.

Results are shown in **Figure SM19** for the historical period, where most ocean regions exhibit low D values, indicating generally good agreement between the fitted non-stationary GEV models and the observed monthly maxima. Future scenarios showed broadly similar diagnostic behavior (not shown).

Reference period ensemble mean

Historical values representative of the reference period were computed using a weighted ensemble mean. Given the uneven representation of downstream wave-model configurations, the driving GCM was treated as the sampling unit, ensuring equal contribution from each GCM independently of the number of associated ensemble members

For each member m , the weight was defined inversely proportional to the number of members originating from its parent GCM so each driving atmospheric model has equal contribution⁹⁰. Let $n_{i,m}$ denote the number of members associated with the GCM i for member m . The raw weight for member m is:

$$w_m = \frac{1/n_{i,m}}{\sum_{m=1}^{m=M} 1/n_{i,m}} \quad \text{Eq. 9}$$

where M is the total number of ensemble members. The weighted ensemble mean of a variable X is then

$$\bar{X} = \sum_M w_m \cdot X_m \quad \text{Eq. 10}$$

For Dir_m, weighted circular means were computed.

Projected change computation

We computed projected changes as percentage changes relative to the reference period except for Dir_m, for which the angular change between the future and reference circular means was calculated. These were obtained using a weighted mean across all ensemble members, so that each driving GCM has equal contribution, following the same procedure as for the reference period ensemble mean (Eq. 9 and Eq. 10).

Uncertainty assessment

We assessed uncertainty in projected changes following the IPCC AR6 framework⁹¹. Projected changes were reported using the weighted ensemble mean as the best estimate. Mean climatologies and wave extremes were assessed separately.

For mean climatologies, a quantitative, ensemble-based assessment was adopted, based on the high level of evidence provided by model performance evaluation and the availability of a large ensemble. The proportion of models for which the projected change exceeded internal variability and agreed on the sign of change was determined. Internal variability for each member was first estimated from the interannual standard deviation of the detrended historical annual series. Following the IPCC AR6 Atlas.1⁹² procedure for cases without piControl simulations, the variability threshold was defined as $\gamma = \sqrt{(2/N)} \times 1.645 \times \delta(1\text{yr})$, where $\delta(1\text{yr})$ is the interannual standard deviation of annual mean values, and N is the length of the climatological averaging window. A model was considered to exceed internal variability when its projected change was larger than this threshold. When 66–80% of models exceeded internal variability and agreed on the sign of change, the change was classified as *likely*; when the percentage exceeded 90%, it was classified as *very likely*.

Projected changes in wave extremes were assessed in terms of confidence rather than likelihood because climate emergence could not be robustly quantified against internal variability. For frequent extremes, although internal variability was quantified using the same procedure applied to mean climatologies, projected changes rarely exceeded this threshold due to the large interannual variability associated with the limited number of exceedances per year. Consequently, confidence does not reflect formal signal emergence relative to internal variability, but rather the consistency of the sign of change across the ensemble. *High confidence* was assigned when a strong inter-model agreement on the sign of change ($\geq 80\%$ of models). *Medium confidence* was assigned when an inter-model agreement on the sign of change in 66–80% of models showed a consistent sign of change. *Low confidence* was assigned in regions with limited agreement ($< 66\%$), indicating that projected changes were dominated by inconsistent model responses.

For changes in low-frequency wave extremes, derived with an Extreme Value Analysis, internal variability could not be estimated following a consistent approach. Confidence levels were determined based on two criteria: (i) model agreement and (ii) the uncertainty of the extreme-

value modeling. To quantify the latter, a bootstrap with replacement was applied to resample the monthly maxima used as inputs to the extreme-value model. To preserve seasonal consistency, bootstrapping was performed independently for each calendar month. 100 bootstrap samples were generated for each ensemble member, and projected changes were computed for all realizations. Let $\hat{p}$ denote the fraction of bootstrap realizations exhibiting a positive change (or, equivalently, the dominant sign of change). A member was considered directionally stable only when the dominant sign was at least twice as frequent as the opposite sign, *i.e.*, when $\max(\hat{p}, 1 - \hat{p}) \geq 2/3$. This criterion ensures that the inferred direction of change is stable under sampling uncertainty in the extreme-value fit, requiring a clear dominance of one sign over the other in the bootstrap distribution. Otherwise, the uncertainty in the extreme-value modeling was considered excessive, and the member was treated as neutral, that is, contributing to the ensemble count but not to the sign-of-change agreement.

Grid points where at least 80% of all available ensemble members were directionally stable and supported the same sign of change were assessed as having *high confidence*. Grid points where this proportion was between 66% and 80% were assessed as having *medium confidence*. In contrast, grid points where fewer than 66% of all available ensemble members were directionally stable and supported the same sign of change were assessed as having *low confidence*, reflecting limited directional stability, inconsistent responses across ensemble members, or a combination of both.

To avoid misinterpretation between the calibrated IPCC uncertainty language and the map-based plotting categories, we explicitly distinguish between the two. The calibrated terminology (likelihood and confidence levels) was used exclusively in the manuscript text to describe the strength of the findings. In contrast, the maps follow the fixed categorical scheme defined in Cross-Chapter Box Atlas.1, which is not intended to reproduce calibrated IPCC terms but to provide a consistent visual representation of model agreement and signal emergence. Consequently, the terminology in the text (likelihood for mean changes, confidence for extremes) and the terminology in the figures (agreement- and robustness-based overlays) should not be interpreted as a direct translation of the map categories shown in the figures.

The representation of uncertainty in the maps followed the IPCC AR6 Cross-Chapter Box Atlas.1 procedure. Changes in mean climatologies and percentiles were evaluated using an adapted Approach C. Changes in extremes, derived from a more elaborate analysis, were assessed using an adapted Approach B. All maps display only the weighted ensemble mean.

Approach C applies two criteria: (i) agreement on the sign of change, and (ii) whether each model's projected change exceeds its internal variability. A *robust change* occurs when $\geq 80\%$ of models agree on the sign and $\geq 66\%$ exceed internal variability. If $\geq 66\%$ exceed internal variability but agreement was $< 80\%$, the change is classified as *conflicting change* (black cross-hatching). When fewer than 66% exceed variability, regions were considered as *no change* or *no robust change*; here we distinguish two cases: *emerging signal but not fully robust change* (agreement $\geq 80\%$, variability exceeded by $< 66\%$, shown with grey diagonal hatching) and *non-robust changes* (agreement $< 80\%$, black diagonal hatching).

The adapted Approach B was applied to threshold exceedances and low-frequency extremes and classifies changes according to inter-model agreement on their sign. For low-frequency extremes, agreement was calculated only among ensemble members whose extreme-value estimates passed the internal robustness criterion based on bootstrap resampling. Directionally unstable members remained in the denominator but contributed to neither sign. For threshold exceedances, agreement was calculated across all ensemble members, since limited detectability relative to internal variability constrains probabilistic interpretation but does not invalidate the directional signal. In both cases, grid points with $\geq 80\%$ agreement were classified as *high-*

agreement change (filled-black stippling), those with 66–80% agreement as *moderate-agreement change* (empty-black stippling), and those with <66% agreement as *low-agreement change* (no overlay). For visual clarity, overlays were applied to the less spatially extensive categories in each approach: hatching identifies changes not classified as robust under Approach C, whereas stippling highlights moderate- and high-agreement changes under Approach B.

In the comparison between changes in mean conditions and extremes, the same adapted Approach B is applied simultaneously to both cases. *High-agreement change* therefore requires that both mean conditions and extremes exhibit >80% agreement in the sign of change (including directional stability for extremes), with the remaining categories defined consistently following the same criteria.

Sea ice

Different sea ice parameterizations have been used across the members of the COWCLIP-3 ensemble (**Table SM3**). Many members apply threshold-type approaches, assuming land (total wave blocking) over a certain sea ice concentration (SIC), with the option to partially block wave propagation for a lower range of SIC. Other approaches follow a frequency-dependent ice-induced wave attenuation method which gradually reduces wave energy under partially sea ice covered areas (particularly for high frequencies).

To minimize the influence of model-dependent sea-ice treatments, we focus primarily on regions with limited wave blocking by sea ice. Rather than using SIC directly, areas were identified according to the proportion of blocked wave outputs, defined as either NaN values, or $H_s < 0.1$ m, depending on the parameterization used by each model. Grid cells were retained only where the percentage of blocked outputs remained below 30%. At the ensemble level, climatological statistics were computed only from grid cells satisfying this criterion across all ensemble members.

For the analysis of threshold exceedances, only strictly complete time series were considered. Ice-related missing or near-zero outputs arise from model-specific sea-ice parameterizations and may interrupt storm events or leave exceedances incomplete. Restricting the analysis to complete time series ensures a consistent identification of exceedances across ensemble members and grid cells.

Coastal assessment

We assessed the potential implications of changes in wave climate along the global coastlines for three types of coastal impacts: flooding, erosion, and damage to coastal infrastructure.

Near-coastal grid cells were identified through a two-stage selection procedure. First, all grid cells were evaluated against the Global Self-Consistent Hierarchical High-Resolution Geography (GSHHG) version 2.3.7 coastline dataset, and the great-circle distance to the nearest coastline segment was computed using a spherical formulation. Grid cells located less than 100 km of the coastline were retained. This mask was then refined through interactive inspection, selectively excluding cells where the automatic criterion was insufficient (*e.g.*, Maritime Continent). This manual curation removed cells along enclosed or semi-enclosed basins, inland water bodies, estuarine regions, and other artefacts arising from coastline complexity or member grid representation.

For each impact, we defined wave-climate-based indicators, used as proxies to infer potential implications for the corresponding impact. For erosion-related impacts, we analyzed changes in Dir_m and mean C_gE . Wave direction is a key control on longshore erosion, as variations in the angle of wave incidence can substantially modify the redistribution of sediment along the coast^{93,94}. Although referred to as erosion throughout the manuscript, this category should be

interpreted as a first-order indicator of potential shoreline response associated with changes in wave-driven longshore erosion, including both erosional and accretional tendencies. In addition, wave energy flux characterizes the amount of energy transported by waves and provides a physically based measure of their potential to mobilize and transport sediment upon reaching the coast⁹⁵.

For flooding-related impacts, we considered changes in the mean magnitude of threshold exceedances above the historical 99th H_s , and in the 95th percentile T_p . Both wave height and period influence wave-induced water level contributions at the coast, including wave setup and run-up⁹⁶. The threshold exceedances of H_s were used to characterize energetic wave conditions typically associated with storm-driven sea states.

For infrastructure-related impacts, we analyzed changes in the 50-year return level of H_s . Extreme wave heights associated with specific return periods are commonly used in the design and assessment of coastal protection infrastructures^{97–99}.

For all indicators (except Dir_m), we identified a potential increase in impact-related risk when there is high inter-model agreement in projecting larger values (*i.e.*, an increase in magnitude). For Dir_m , we interpreted robust changes in magnitude (either positive or negative) as an alteration of the wave forcing relevant to coastal processes, without implying a deterministic increase or decrease in impact severity. We evaluated indicators independently, and a high inter-model agreement change in at least one indicator was interpreted as a signal of wave-climate sensitivity of the coastal system. We considered a high inter-model agreement change when more than 80% of members agreed on the sign of change. Coastal regions meeting this criterion were referred to as *wave-climate-sensitive coastal regions*. Within these regions, regions where all indicators associated with a given impact exhibited high inter-model agreement changes were highlighted as *wave-climate-sensitive coastal hotspots* for that impact.

References

1. Toimil, A., Álvarez-Cuesta, M. & Losada, I. J. Neglecting the effect of long- and short-term erosion can lead to spurious coastal flood risk projections and maladaptation. *Coastal Engineering* 179, (2023).
2. Toimil, A., Losada, I. J., Álvarez-Cuesta, M. & Le Cozannet, G. Demonstrating the value of beaches for adaptation to future coastal flood risk. *Nat. Commun.* 14, (2023).
3. Garzon, J. L. *et al.* Conceptual and quantitative categorization of wave-induced flooding impacts for pedestrians and assets in urban beaches. *Sci. Rep.* 13, (2023).
4. Idier, D., Bertin, X., Thompson, P. & Pickering, M. D. Interactions Between Mean Sea Level, Tide, Surge, Waves and Flooding: Mechanisms and Contributions to Sea Level Variations at the Coast. *Surveys in Geophysics* vol. 40 1603–1630 Preprint at <https://doi.org/10.1007/s10712-019-09549-5> (2019).
5. Kirezci, E., Young, I. R., Ranasinghe, R., Lincke, D. & Hinkel, J. Global-scale analysis of socioeconomic impacts of coastal flooding over the 21st century. *Front. Mar. Sci.* 9, (2023).
6. Alvarez-Cuesta, M., Toimil, A. & Losada, I. J. Modelling long-term shoreline evolution in highly anthropized coastal areas. Part 1: Model description and validation. *Coastal Engineering* 169, 103960 (2021).
7. Toimil, A. *et al.* Climate change-driven coastal erosion modelling in temperate sandy beaches: Methods and uncertainty treatment. *Earth-Science Reviews* vol. 202 Preprint at <https://doi.org/10.1016/j.earscirev.2020.103110> (2020).
8. Ghanavati, M. *et al.* An assessment of whether long-term global changes in waves and storm surges have impacted global coastlines. *Sci. Rep.* 13, (2023).
9. Rahman, J., Aghaeidoost, V. & Billah, A. M. Resilience of coastal bridges under extreme wave-induced loads. *Resilient Cities and Structures* 3, 85–100 (2024).
10. Dong, J., Asif, Z., Shi, Y., Zhu, Y. & Chen, Z. Climate Change Impacts on Coastal and Offshore Petroleum Infrastructure and the Associated Oil Spill Risk: A Review. *Journal of Marine Science and Engineering* vol. 10 Preprint at <https://doi.org/10.3390/jmse10070849> (2022).
11. Cosby, A. G. *et al.* Accelerating growth of human coastal populations at the global and continent levels: 2000–2018. *Sci. Rep.* 14, (2024).
12. Reimann, L., Vafeidis, A. T. & Honsel, L. E. Population development as a driver of coastal risk: Current trends and future pathways. *Cambridge Prisms: Coastal Futures* vol. 1 Preprint at <https://doi.org/10.1017/cft.2023.3> (2023).
13. Rogers, J. S., Maneta, M. M., Sain, S. R., Madaus, L. E. & Hacker, J. P. The role of climate and population change in global flood exposure and vulnerability. *Nature Communications* 16, (2025).

- 668 14. McGranahan, G., Balk, D. & Anderson, B. The rising tide: Assessing the risks of
669 climate change and human settlements in low elevation coastal zones. *Environ.*
670 *Urban.* 19, 17–37 (2007).
- 671 15. Melet, A., Meyssignac, B., Almar, R. & Le Cozannet, G. Under-estimated wave
672 contribution to coastal sea-level rise. *Nat. Clim. Chang.* 8, 234–239 (2018).
- 673 16. Storlazzi, C. D. *et al.* *O C E A N O G R A P H Y* Most Atolls Will Be
674 *Uninhabitable by the Mid-21st Century Because of Sea-Level Rise Exacerbating*
675 *Wave-Driven Flooding.* <https://www.science.org> (2018).
- 676 17. Peter Sheng, Y., Paramygin, V. A., Yang, K. & Rivera-Nieves, A. A.
677 sensitivity study of rising compound coastal inundation over large flood plains in
678 a changing climate. *Sci. Rep.* 12, (2022).
- 679 18. Sobel, A. H. *et al.* *Human Influence on Tropical Cyclone Intensity NATURAL*
680 *HAZARDS.* vol. 242 <https://www.science.org> (2016).
- 681 19. Pérez-Alarcón, A., Fernández-Alvarez, J. C. & Coll-Hidalgo, P. Global Increase
682 of the Intensity of Tropical Cyclones under Global Warming Based on their
683 Maximum Potential Intensity and CMIP6 Models. *Environmental Processes* 10,
684 (2023).
- 685 20. Balaguru, K. *et al.* A Global Increase in Nearshore Tropical Cyclone
686 Intensification. *Earths Future* 12, (2024).
- 687 21. Masson-Delmotte, V. *et al.* Climate change 2021: the physical science basis.
688 *Contribution of working group I to the sixth assessment report of the*
689 *intergovernmental panel on climate change* 2, 2391 (2021).
- 690 22. World Meteorological Organization. *The 2022 GCOS ECVs Requirements.*
691 <https://library.wmo.int/idurl/4/58111> (2022).
- 692 23. Casas-Prat, M., Wang, X. L. & Sierra, J. P. A physical-based statistical method
693 for modeling ocean wave heights. *Ocean Model. (Oxf).* 73, 59–75 (2014).
- 694 24. Camus, P. *et al.* Statistical wave climate projections for coastal impact Earth ' s
695 Future. *Earth ' s Future* <https://doi.org/10.1002/ef2.234> (2017)
696 doi:10.1002/ef2.234.
- 697 25. Perez, J., Menendez, M., Camus, P., Mendez, F. J. & Losada, I. J. Statistical
698 multi-model climate projections of surface ocean waves in Europe. *Ocean Model.*
699 *(Oxf).* 96, 161–170 (2015).
- 700 26. Hemer, M. A., Fan, Y., Mori, N., Semedo, A. & Wang, X. L. Projected changes
701 in wave climate from a multi-model ensemble. *Nat. Clim. Chang.* 3, 471–476
702 (2013).
- 703 27. Hemer, M. A., Katzfey, J. & Trenham, C. E. Global dynamical projections of
704 surface ocean wave climate for a future high greenhouse gas emission scenario.
705 *Ocean Model. (Oxf).* 70, 221–245 (2013).

- 706 28. Mori, N., Shimura, T., Yasuda, T. & Mase, H. Multi-model climate projections
707 of ocean surface variables under different climate scenarios-Future change of
708 waves, sea level and wind. *Ocean Engineering* 71, 122–129 (2013).
- 709 29. Semedo, A. *et al.* Projection of global wave climate change toward the end of the
710 twenty-first century. *J. Clim.* 26, 8269–8288 (2013).
- 711 30. Fan, Y., Held, I. M., Lin, S. J. & Wang, X. L. Ocean warming effect on surface
712 gravity wave climate change for the end of the twenty-first century. *J. Clim.* 26,
713 6046–6066 (2013).
- 714 31. Fan, Y., Lin, S. J., Griffies, S. M. & Hemer, M. A. Simulated global swell and
715 wind-sea climate and their responses to anthropogenic climate change at the end
716 of the twenty-first century. *J. Clim.* 27, 3516–3536 (2014).
- 717 32. Casas-Prat, M., Wang, X. L. & Swart, N. CMIP5-based global wave climate
718 projections including the entire Arctic Ocean. *Ocean Model. (Oxf)*. 123, 66–85
719 (2018).
- 720 33. Erikson, L. H., Hegermiller, C. A., Barnard, P. L., Ruggiero, P. & van Ormondt,
721 M. Projected wave conditions in the Eastern North Pacific under the influence of
722 two CMIP5 climate scenarios. *Ocean Model. (Oxf)*. 96, 171–185 (2015).
- 723 34. Wang, X. L., Feng, Y. & Swail, V. R. Changes in global ocean wave heights as
724 projected using multimodel CMIP5 simulations. *Geophys. Res. Lett.* 41, 1026–
725 1034 (2014).
- 726 35. Dobrynin, M., Murawsky, J. & Yang, S. Evolution of the global wind wave
727 climate in CMIP5 experiments. *Geophys. Res. Lett.* 39, 2–7 (2012).
- 728 36. Dobrynin, M., Murawski, J., Baehr, J. & Ilyina, T. Detection and attribution of
729 climate change signal in ocean wind waves. *J. Clim.* 28, 1578–1591 (2015).
- 730 37. Kamranzad, B. & Mori, N. Future wind and wave climate projections in the
731 Indian Ocean based on a super-high-resolution MRI-AGCM3.2S model
732 projection. *Clim. Dyn.* 53, 2391–2410 (2019).
- 733 38. Morim, J., Hemer, M., Cartwright, N., Strauss, D. & Andutta, F. On the
734 concordance of 21st century wind-wave climate projections. *Glob. Planet.*
735 *Change* 167, 160–171 (2018).
- 736 39. Lemos, G., Semedo, A., Hemer, M., Menendez, M. & Miranda, P. M. A. Remote
737 climate change propagation across the oceans - The directional swell signature.
738 *Environmental Research Letters* 16, (2021).
- 739 40. Lemos, G. *et al.* Mid-twenty-first century global wave climate projections:
740 Results from a dynamic CMIP5 based ensemble. *Glob. Planet. Change* 172, 69–
741 87 (2019).
- 742 41. Kumar, R., Lemos, G., Semedo, A. & Li, J. G. A global high-resolution CMIP6
743 ensemble of wave climate simulations and projections using a coastal multigrid:
744 Configuration and performance evaluation. *Ocean Model. (Oxf)*. 197, (2025).

- 745 42. Meucci, A., Young, I. R., Trenham, C. & Hemer, M. An 8-model ensemble of
746 CMIP6-derived ocean surface wave climate. *Sci. Data* 11, (2024).
- 747 43. Meucci, A., Young, I. R., Hemer, M., Trenham, C. & Watterson, I. G. 40 Years
748 of Global Ocean Wind-Wave Climate Derived from CMIP6 ACCESS-CM2 and
749 EC-Earth3 GCMs: Global Trends, Regional Changes, and Future Projections.
750 <https://doi.org/10.1175/JCLI-D-21> doi:10.1175/JCLI-D-21.
- 751 44. Lobeto, H. *et al.* On the assessment of the wave modeling uncertainty in wave
752 climate projections. *Environmental Research Letters* 18, (2023).
- 753 45. Lemos, G. *et al.* Performance evaluation of a global CMIP6 single forcing, multi
754 wave model ensemble of wave climate simulations. *Ocean Model. (Oxf)*. 102237
755 (2023) doi:10.1016/j.ocemod.2023.102237.
- 756 46. Kumar, R., Lemos, G., Semedo, A. & Alsaaq, F. Parameterization-Driven
757 Uncertainties in Single-Forcing, Single-Model Wave Climate Projections from a
758 CMIP6-Derived Dynamic Ensemble. *Climate* 10, (2022).
- 759 47. Casas-Prat, M. *et al.* CanESM5-derived ocean wave projections —
760 Considerations for coarse resolution climate models. *Ocean Model. (Oxf)*. 192,
761 (2024).
- 762 48. Morim, J. *et al.* Robustness and uncertainties in global multivariate wind-wave
763 climate projections. *Nat. Clim. Chang.* 9, 711–718 (2019).
- 764 49. Morim, J. *et al.* A global ensemble of ocean wave climate projections from
765 CMIP5-driven models. *Sci. Data* 7, 1–10 (2020).
- 766 50. Lobeto, H., Menendez, M. & Losada, I. J. Future behavior of wind wave
767 extremes due to climate change. *Sci. Rep.* 11, 1–12 (2021).
- 768 51. Meucci, A., Young, I. R., Hemer, M., Kirezci, E. & Ranasinghe, R. Projected
769 21st century changes in extreme wind-wave events. *Sci. Adv* 6, 7295–7305
770 (2020).
- 771 52. Mori, N., Yasuda, T., Mase, H., Tom, T. & Oku, Y. Projection of Extreme Wave
772 Climate Change under Global Warming. 19, 15–19 (2010).
- 773 53. O’Grady, J. G., Hemer, M. A., McInnes, K. L., Trenham, C. E. & Stephenson, A.
774 G. Projected incremental changes to extreme wind-driven wave heights for the
775 twenty-first century. *Sci. Rep.* 11, 1–8 (2021).
- 776 54. Caires, S., Swail, V. R. & Wang, X. L. Projection and analysis of extreme wave
777 climate. *J. Clim.* 19, 5581–5605 (2006).
- 778 55. Hersbach, H. *et al.* The ERA5 global reanalysis. *Quarterly Journal of the Royal
779 Meteorological Society* 146, 1999–2049 (2020).
- 780 56. Piollé, J.-F., Dodet, G. & Quilfen, Y. ESA Sea State Climate Change Initiative
781 (Sea_State_cci) : Global remote sensing merged multi-mission monthly gridded
782 significant wave height from altimetry, L4 product, version 3. Preprint at
783 <https://doi.org/10.5285/9C350D4FF7EE438F9F1FC7252CBB2282> (2022).

- 784 57. Harvey, B., Cook, P., Shaffrey, L. C. & Schiemann, R. The response of the
785 Northern Hemisphere storm tracks and jetstreams to climate change in the
786 CMIP3, CMIP5, and CMIP6 climate models. *Journal of Geophysical Research*
787 (*Atmospheres*) 0–3 (2020) doi:10.1029/2020JD032701.
- 788 58. Priestley, M. D. K. *et al.* An Overview of the Extratropical Storm Tracks in
789 CMIP6 Historical Simulations. *J. Clim.* 33, 6315–6343 (2020).
- 790 59. Tamarin, T. & Kaspi, Y. The poleward shift of storm tracks under global
791 warming: A Lagrangian perspective. *Geophys. Res. Lett.* 44, 10,666–10,674
792 (2017).
- 793 60. Chemke, R. & Yuval, J. Climate change shifts the North Pacific storm track
794 polewards. *Nature* 649, 626–630 (2026).
- 795 61. Martinez, A. & Iglesias, G. Global wind energy resources decline under climate
796 change. *Energy* 288, (2024).
- 797 62. Lemos, G., Menendez, M., Semedo, A., Miranda, P. M. A. & Hemer, M. On the
798 decreases in North Atlantic significant wave heights from climate projections.
799 *Clim. Dyn.* 57, 2301–2324 (2021).
- 800 63. Tamarin-Brodsky, T. & Kaspi, Y. Enhanced poleward propagation of storms
801 under climate change. *Nat. Geosci.* 10, 908–913 (2017).
- 802 64. Deng, K. *et al.* Changes of Southern Hemisphere westerlies in the future
803 warming climate. *Atmos. Res.* 270, (2022).
- 804 65. Goyal, R., Sen Gupta, A., Jucker, M. & England, M. H. Historical and Projected
805 Changes in the Southern Hemisphere Surface Westerlies. *Geophys. Res. Lett.* 48,
806 (2021).
- 807 66. Lobeto, H., Menendez, M., Losada, I. J. & Hemer, M. The effect of climate
808 change on wind-wave directional spectra. *Glob. Planet. Change* 213, (2022).
- 809 67. Li, D. Y., Reed, K. A., Zarzycki, C. M. & Camargo, S. J. Robust responses of
810 tropical and post-tropical cyclones to climate warming in WRF and CAM
811 storyline ensembles. *Weather Clim. Extrem.* 52, (2026).
- 812 68. Grossmann-Matheson, G., Young, I. R., Meucci, A. & Alves, J. H. Global
813 changes in extreme tropical cyclone wave heights under projected future climate
814 conditions. *Sci. Rep.* 14, (2024).
- 815 69. Appendini, C. M. *et al.* Redefining design wave conditions in the Gulf of Mexico
816 under a changing climate. *Ocean Engineering* 334, (2025).
- 817 70. Oppenheimer, M. *et al.* Sea Level Rise and Implications for Low Lying Islands,
818 Coasts and Communities. *IPCC Special Report on the Ocean and Cryosphere in*
819 *a Changing Climate* 355, (2019).
- 820 71. Chemke, R., Zanna, L., Orbe, C., Sentman, L. T. & Polvani, L. M. The Future
821 Intensification of the North Atlantic Winter Storm Track: The Key Role of

822 Dynamic Ocean Coupling. <https://doi.org/10.1175/JCLI-D-21> doi:10.1175/JCLI-
823 D-21.

824 72. Zappa, G., Shaffrey, L. C., Hodges, K. I., Sansom, P. G. & Stephenson, D. B. A
825 Multimodel Assessment of Future Projections of North Atlantic and European
826 Extratropical Cyclones in the CMIP5 Climate Models*.
827 <https://doi.org/10.1175/JCLI-D> doi:10.1175/JCLI-D.

828 73. Cao, X. *et al.* The Projected Poleward Shift of Tropical Cyclogenesis at a Global
829 Scale Under Climate Change in MRI-AGCM3.2H. *Geophys. Res. Lett.* 51,
830 (2024).

831 74. Chang, E. K. M. Projected Significant Increase in the Number of Extreme
832 Extratropical Cyclones in the Southern Hemisphere.
833 <https://doi.org/10.1175/JCLI-D-16-0553.s1> doi:10.1175/JCLI-D-16-0553.s1.

834 75. Chemke, R., Ming, Y. & Yuval, J. The intensification of winter mid-latitude
835 storm tracks in the Southern Hemisphere. *Nat. Clim. Chang.* 12, 553–557 (2022).

836 76. Francis, D. & Fonseca, R. Recent and projected changes in climate patterns in the
837 Middle East and North Africa (MENA) region. *Sci. Rep.* 14, (2024).

838 77. Jain, S., Mishra, S. K., Anand, A., Salunke, P. & Fasullo, J. T. Historical and
839 projected low-frequency variability in the Somali Jet and Indian Summer
840 Monsoon. *Clim. Dyn.* 56, 749–765 (2021).

841 78. Luijendijk, A. *et al.* The State of the World’s Beaches. *Sci. Rep.* 8, (2018).

842 79. Mentaschi, L., Vousedoukas, M. I., Pekel, J. F., Voukouvalas, E. & Feyen, L.
843 Global long-term observations of coastal erosion and accretion. *Sci. Rep.* 8,
844 (2018).

845 80. Vousedoukas, M. I. *et al.* Sandy coastlines under threat of erosion. *Nature Climate*
846 *Change* vol. 10 260–263 Preprint at <https://doi.org/10.1038/s41558-020-0697-0>
847 (2020).

848 81. Izaguirre, C., Losada, I. J., Camus, P., Vigh, J. L. & Stenek, V. Climate change
849 risk to global port operations. *Nat. Clim. Chang.* 11, 14–20 (2021).

850 82. Allshop, N. W. H., Cork, R. S. & Jan Verhagen, H. A database of major
851 breakwaters aroundf the world. in (2009).

852 83. Fyke, J., Swart, N. C. & Huard, D. An Earth System Model Ensemble Forced
853 With Probabilistic Emissions: Demonstration and Prospects for Climate Risk
854 Assessment. *Earths Future* 14, (2026).

855 84. Hersbach, H. *et al.* The ERA5 global reanalysis. *Quarterly Journal of the Royal*
856 *Meteorological Society* 146, 1999–2049 (2020).

857 85. Laface, V. & Arena, F. On correlation between wind and wave storms. *J. Mar.*
858 *Sci. Eng.* 9, (2021).

859 86. Lobeto, H. *et al.* Global coastal wave storminess. *Sci. Rep.* 14, (2024).

87. Méndez, F. J., Menéndez, M., Luceño, A. & Losada, I. J. Analyzing monthly extreme sea levels with a time-dependent GEV model. *J. Atmos. Ocean. Technol.* 24, 894–911 (2007).
88. Menéndez, M. & Woodworth, P. L. Changes in extreme high water levels based on a quasi-global tide-gauge data set. *J. Geophys. Res. Oceans* 115, (2010).
89. Lobeto, H. & Menendez, M. Variability Assessment of Global Extreme Coastal Sea Levels Using Altimetry Data. *Remote Sens. (Basel)*. 16, (2024).
90. Casas-Prat, M. *et al.* Wind-wave climate changes and their impacts. *Nature Reviews Earth and Environment* vol. 5 23–42 Preprint at <https://doi.org/10.1038/s43017-023-00502-0> (2024).
91. Masson-Delmotte, V. *et al.* *IPCC, 2021: Climate Change 2021: The Physical Science Basis. Cambridge University Press. In Press.* (2021).
92. Gutiérrez, J. M. , J. R. G. , N. G. T. , A. L. M. , A. M. , G. I. V. , ... Y. J.-H. (2021). *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change.*
93. Harley, M. D. *et al.* Extreme coastal erosion enhanced by anomalous extratropical storm wave direction. *Sci. Rep.* 7, 1–9 (2017).
94. Splinter, K. D., Turner, I. L., Reinhardt, M. & Ruessink, G. Rapid adjustment of shoreline behavior to changing seasonality of storms: observations and modelling at an open-coast beach. *Earth Surf. Process. Landf.* 42, 1186–1194 (2017).
95. (US), C. E. R. C. *Shore Protection Manual*. vol. 1 (Department of the Army, Waterways Experiment Station, Corps of Engineers~..., 1984).
96. Stockdon, H. F., Holman, R. A., Howd, P. A. & Sallenger, A. H. Empirical parameterization of setup, swash, and runup. *Coastal Engineering* 53, 573–588 (2006).
97. Losada, M. A. & Gimenez-Curto, L. A. The joint effect of the wave height and period on the stability of rubble mound breakwaters using Iribarren’s number. *Coastal Engineering* 3, 77–96 (1979).
98. Van der Meer, J. W. Stability of breakwater armour layers — design formulae. *Coastal Engineering* 11, 219–239 (1987).
99. Goda, Y. *Random Seas and Design of Maritime Structures*. vol. 33 (World Scientific Publishing Company, 2010).

Figures

Figure 1: Global ensemble bias assessment. Mean bias relative to ERA5 reanalysis in (a) mean H_s , (b) the 95th percentile of H_s , (c) the monthly variability index (see Methods), and (d) the interannual variability index (see Methods). The panels above and beside each map show the 25th (dark gray) and 75th (pink) percentiles of the inter-model standard deviation as a function of longitude (horizontal panels) and latitude (vertical panels). The number of ensemble members used in the calculation is indicated in **Table SM2**.

Figure 2: Projected changes in mean wave climatologies. Historical ensemble mean of (a) mean H_s , (b) mean T_p , (c) mean $C_g E$ and (d) mean Dir_m . Projected changes in (e, i, m, q) mean H_s , (f, j, n, r) mean T_p , (g, k, o, s) mean $C_g E$, and (h, l, p, t) mean Dir_m . Changes are shown for the SSP1–2.6 (e–l) and SSP5–8.5 (m–t) scenarios. Projected changes in scalar variables are expressed as relative changes for mid-century (2036–2065; e–h, m–p) and end-century (2071–2100; i–l, q–t) relative to the reference period (1985–2014). Projected changes in Dir_m are expressed as absolute changes (degrees) for the same time horizons. *Robust change* is shown without hatching; *conflicting change* with black cross-hatching; *emerging but not fully robust change* with gray diagonal hatching; and *non-robust change* with black diagonal hatching (see Methods for a full description of the uncertainty representation). The number of ensemble members used in the calculation is indicated in **Table SM2**.

Figure 3: Projected changes in threshold exceedances. Historical ensemble mean (a) annual frequency of occurrence and (b) mean exceedance magnitude above the historical 99th percentile of H_s . Projected changes in (c–f) annual frequency of occurrence and (g–j) mean exceedance magnitude. Changes are shown for the SSP1–2.6 (c–d, g–h) and SSP5–8.5 (e–f, i–j) scenarios. Projected changes are expressed as changes for mid-century (2036–2065; c, e, g, i) and end-century (2071–2100; d, f, h, j) relative to the reference period (1985–2014). *High-agreement change* is shown with filled black stippling; *moderate-agreement change* with empty black stippling; and *low-agreement change* without overlay (see Methods for a full description of the uncertainty representation). The number of ensemble members used in the calculation is indicated in **Table SM2**.

Figure 4: Projected changes in return levels and return periods. (a) Historical ensemble mean 50-year return level of H_s . (b–e) Projected changes in the 50-year return level of H_s and (f–i) projected return periods of the historical 50-year return level of H_s . Results are shown for the SSP1–2.6 (b–c, f–g) and SSP5–8.5 (d–e, h–i) scenarios. Projected changes are expressed as relative changes for mid-century (2036–2065; a, c) and end-century (2071–2100; b, d) relative to the reference period (1985–2014). Future return periods are shown for the same scenarios and time horizons (in years). *High-agreement change* is shown with filled black stippling; *moderate-agreement change* with empty black stippling; and *low-agreement change* without overlay (see Methods for a full description of the uncertainty representation). The number of ensemble members used in the calculation is indicated in **Table SM2**.

Figure 5: Consistency between projected changes in mean and extreme wave heights. Projected changes in mean conditions are represented by changes in mean H_s . Projected changes in extreme conditions are represented by changes in the 50-year return level of H_s . Colors indicate the different combinations of the signs of change for mean and extreme wave conditions. Changes are assessed for the SSP1–2.6 (a, c) and SSP5–8.5 (b, d) scenarios, for mid-century (2036–2065; a–b) and end-century (2071–2100; c–d) relative to the reference period (1985–2014). *High-agreement change* is shown with filled black stippling; *moderate-agreement change* with empty black stippling; and *low-agreement change* without overlay (see Methods for a full description of the uncertainty representation).

Figure 6: Coastal sensitivity to wave climate changes. Colors indicate coastal regions where projected changes in wave-climate indicators are associated with increased sensitivity to flooding, erosion, or infrastructure damage, with more than 80% of ensemble members agreeing on the sign of change. Light-grey coastal segments indicate that none of the indicators met this criterion. For circular variables, no distinction is made between directions of rotation.