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Title
Robustness and uncertainties in global multivariate wind-wave climate projections

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Robustness and uncertainties in global multivariate wind-wave climate projections

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Introductory Paragraph (abstract)

Understanding climate-driven impacts on the multivariate global wind-wave climate is paramount to effective offshore/coastal climate adaptation planning. However, the use of single-method ensembles and variations arising from different methodologies, has resulted in unquantified uncertainty amongst existing global wave climate projections. Here, assessing the first coherent, community-driven multi-method ensemble of global wave climate projections, we show widespread ocean regions with robust changes in annual mean significant wave height ($\acute{H}_s$) and mean wave period ($\acute{T}_m$) of 5-15% and shifts in mean wave direction ($\acute{\theta}_m$) of 5-15 degrees, under a high emission scenario. Approximately 50% of the world's coastline is at risk of wave climate change with ~40% revealing robust changes in at least two variables. Further, we find that uncertainty in current projections is dominated by climate model-driven uncertainty, and that single-method modelling studies are unable to capture up to ~50% of the total associated uncertainty.

Main body

Wind-waves are dominant contributors to coastal sea-level dynamics[1,2] and shoreline stability[3-5], and can be major disruptors of coastal population[6], marine ecosystems[7] and offshore/coastal infrastructures. Future changes to the multivariate global wind-wave climate (H_s, T_m and θ_m) result from a combination of meteorologically-driven changes in ocean surface wind fields[6,8] and morphologically-driven changes nearshore (combined effects of changes in sea-level[9], tides, reef structures[10] with long-term changes in beach morphology[11]). These changes might potentially exacerbate[12,13], or even exceed in some coastal regions[1,14-16], impacts of future projected sea-level rise. The impacts could be further exacerbated when considering directional changes in wave propagation (θ_m) which is a major driver of coastal stability at all time-scales[5,9,13,17]. Establishing robust projections of global wave characteristics (by identifying and

122 assessing regions with lack of climate signal and/or inter-member agreement)
123 (see Methods section 5)[18] and quantifying the uncertainties introduced by the
124 complex modelling processes used for that purpose, is paramount to prevent
125 potentially costly maladaptation[19,20]. A problem, however, arises from the wide
126 range of wind-wave methodologies used to derive wave characteristics from
127 surface winds or pressure fields, which increases the poorly-understood
128 uncertainty in existing projections[21-23]. Consequently, the
129 the United Nations Intergovernmental Panel on Climate Change (herein IPCC)
130 Fifth Assessment Report (AR5)[24] assigned low confidence to wave projections
131 (with medium confidence for Southern Ocean H_s increase), owing to the limited
132 number of available model simulations and the uncertainty surrounding Global
133 Climate Model (GCM) downscaled surface winds.
134   Since then, a new generation of global wind-wave projection studies have been
135 completed by several international modelling groups[25-34] using atmospheric
136 forcing fields obtained from the Coupled Model Intercomparison Project Phase 5
137 (CMIP5) GCM simulations. While each of these independent studies has
138 considered aspects of the uncertainty related to their own specific climate-
139 modelling process, they treated the uncertainty space very differently (such as
140 emission scenarios and/or GCMs). Furthermore, no studies quantified the
141 uncertainty introduced by their own particular wind-wave modelling method
142 (WMM) to develop global wind-wave fields. This uncertainty stems from different
143 configurations of statistical approaches (including transfer functions, training
144 datasets and predictor corrections) and/or dynamical wind-wave models
145 (including source-term parameterizations, sea-ice fields and numerical
146 resolution) (Supplementary Table S1).
147   Consequently, these studies present contrasting projected changes in wind-
148 wave characteristics (in terms of magnitude and/or signal) across the world's
149 ocean[21]. Such limitations might have potentially hampered broad-scale
150 assessments of future coastal risk and vulnerability[1,22]. These assessments have
151 either used future H_s changes derived from a very limited number of GCM-forced
152 global wind-wave simulations surrounded by low confidence[35,36], or have
153 neglected any future wave changes[37,38] on the basis of the unavailability of
154 robust global data[39] and the high uncertainty between existing studies[40].
155   Here, we seek to minimize such limitations by performing a unique analysis of
156 a coordinated multi-method ensemble of future global wave climate scenarios
157 derived from ten independent state-of-the-art studies[25-34]; which have been
158 undertaken under a pre-designed, community-driven framework[41,42]. Combined,
159 these studies yield a large ensemble of 148 members of global wave-climate
160 projections, from which we identify robust projected meteorologically-driven
161 changes in H_s, T_m and θ_m at global scale. Further, this multi-method ensemble of
162 wave projections enables us to quantify (and compare), for the first time, all

163   three dominant sources of uncertainty (emission scenarios, global climate
164   models and wind-wave modelling methods); which has not been previously
165   attempted owing to lack of multi-method ensembles.
166   Two[33,34] of the ten contributing studies employ different statistical approaches
167   to derive global wave projections exploiting relationships between GCM-
168   simulated sea-level pressure (SLP) fields and wave parameters. The remaining
169   contributions[25-32] use different configurations of dynamical approaches, in which
170   GCM-simulated high-temporal resolution near-surface winds are directly used to
171   drive a global wind-wave model. Consult the Supplementary Information (Section
172   1.1, and Table S1) for the details of each contribution and respective acronyms.
173   All the contributing studies[25-34] have provided assessments of the performance
174   of their GCM-forced wave simulations to represent the historical wave climate on
175   an independent basis. Here, we compare the model-skill of each ensemble
176   member, against the most recent and complete, calibrated dataset of satellite
177   altimeter H_s measurements of H_s[43]. In addition, we compare the model-skill
178   against the well-validated[44] ERA-Interim[45] (ERAI) multivariate (H_s, T_m, θ_m) wave
179   reanalysis for the present-day time-slice (1979-2004) as a common reference
180   dataset. The details of the two databases are described in the Methods (Section
181   2). We present our model-skill comparisons using Taylor diagrams[46] at both
182   global- and regional-scale, providing spatial correlation (SC), normalized
183   standard deviation (NSD) as well as centred-root-mean-square-difference
184   (CRMSD) within a single diagram. To further support our model skill analysis, we
185   provide global pairwise comparisons maps of the mean and variability biases for
186   a subset with common forcing GCM-WMM (Supplementary Table S3, Section 5).
187   Overall, both dynamical and statistical-based simulations exhibit good
188   agreement relative to satellite measurements and ERAI. CRMSD values in
189   annual/seasonal $\acute{H}_s$ are generally below 0.5 m, with NSD values below 0.5 m and
190   SC values above 0.9 at global- and regional-scales, regardless of the reference
191   dataset used here (Supplementary Figs. S1-S4, S6-S8). The agreement in annual
192   mean 99th percentile significant wave height (H_s^{99}) is relatively similar to that
193   seen for $\acute{H}_s$. However, we find relatively less model-skill in representing annual
194   H_s^{99} at regional-scale, particularly across the South Atlantic/Pacific and Southern
195   Indian Ocean with NSD values up to ~1 m (Supplementary Fig. S5). The bias
196   values in annual $\acute{H}_s$ and H_s^{99} relative to satellite data are usually under ~10-15%
197   and ~15-17.5% over the global ocean, respectively (Supplementary Figs. S12-
198   S13). The ensemble mean of each study exhibits biases of less than ~5% in
199   annual $\acute{H}_s$ anywhere, respectively. Comparison against the ERAI data in terms of
200   annual/seasonal $\acute{T}_m$ and $\acute{\theta}_m$ exhibits good agreement, with the CRMSD values
201   under 0.5 s and 0.75°, respectively, and SC values above 0.9 (Supplementary
202   Figs. S6-S8), at both global and regional-scale (Supplementary Fig. S9). Further

203 discussion on the model-skill at seasonal, regional and inter-annual scales is
204 provided in the Supplementary Information (Section 3 and 5).
205   Cluster analysis of $\acute{H}_s$ by member (Methods, Section 3.1) over the present-day
206 time-slice delineates groups of ensemble members defined by wave-modelling
207 methodology, rather than the GCM-forcing (Fig. 1). These results supported by
208 Fig. S12 show that WMM strongly dominates the variance in this community
209 ensemble of historical wave simulations (which includes all GCM-forced wave
210 simulated data available to date). Within each WMM cluster, we note close
211 association of members with similar GCM-forcing (that is, GCMs with shared
212 dynamical cores).
213   Fig. 1 shows two well-defined statistically-derived clusters (1 and 5) explained
214 by differences in the training datasets, transfer functions and/or predictor
215 corrections, and three dynamically-based clusters (2-3 and 4) arising from
216 differences in dynamical wave modelling configurations (e.g., model source-term
217 parameterizations). Note that clusters 1 (IHC) and 5 (ECCC (s)) share a common
218 characteristics, in which their members have very high similarity, as a
219 consequence of their statistical calibrations and predictor corrections[33,47]. This is
220 also evident in our model-skill comparison (Supplementary Figs. S1-S3, S12).
221 Consult Supplementary Information (Section 4) for the details on the distinctive
222 qualities of each cluster and for discussion on within-cluster similarities.
223   Projected future changes in the climatological mean wave fields over the globe
224 by the end of the 21st century (2081-2100) are assessed for two representative
225 concentration pathways: a medium (RCP4.5) and a high-emission scenario
226 (RCP8.5). The RCP4.5 and RCP8.5 exhibit very similar spatial patterns of
227 projected changes for all wave parameters but the RCP8.5 shows relatively
228 larger changes (Fig. 2). Signals of projected changes in annual mean wave
229 parameters ($\acute{H}_s$, $\acute{T}_m$, and $\acute{\theta}_m$) shows robust change (Methods, Section 5) over
230 ~36%, 44% and 32% of global ocean, respectively (under RCP8.5) (Table S2).
231   A robust projected decrease in annual $\acute{H}_s$ is seen across the North Atlantic
232 Ocean and portions of the northern Pacific Ocean of up to ~10% under RCP8.5,
233 expanding further across the eastern Indian and southern Atlantic Oceans in
234 Austral summer. This is consistent with the relatively uniform decrease in
235 projected surface wind speeds over the boreal extra-tropical storm belt[48] partially
236 driven by a strongly reduced meridional temperature gradient due to the polar
237 amplification of climate change[49]. The areas of robust projected increase are
238 limited to the Southern Ocean and the tropical eastern Pacific - in line with the
239 intensification and poleward shift of the austral westerly storm belt[50] and
240 increasing Southern Ocean swell propagation into the tropical areas[23]
241 respectively. In the Austral winter, regions of robust projected increase expand
242 further across the tropics. These findings are overall qualitatively consistent with

243   the Coordinated Ocean Wave Climate Project (COWCLIP) CMIP3 multi-model

244   ensemble[23], and other relevant literature[21].

245   Storm significant wave height H_s^{99} show similar annual/seasonal characteristics

246   of change as for $\acute{H}_s$, however, the fraction of global ocean showing robust

247   changes is much smaller (Fig. 2, Supplementary Table S2) highlighting the high

248   uncertainty in extreme wave climate projections. Although we present changes

249   in projected changes in extreme H_s^{99}, we draw attention to the ongoing challenge

250   of resolving storm wave conditions generated by intense tropical/extra-tropical

251   storms in wave simulations forced directly with atmospheric surface fields (~1-

252   2°) from CMIP5 GCMs. High-resolution studies[33,34] have highlighted the

253   importance of increased wind forcing resolution (~0.25°) to adequately capture

254   storm wave climate in tropical cyclone-affected areas, and the sensitivity of

255   projected changes to resolution.

256   The extended influence of the increasing propagation of swells from the

257   Southern Ocean region into the tropics is shown by the robust projected increase

258   in $\acute{T}_m$ (~44% of the global ocean region) and the projected shift in $\acute{\theta}_m$ over ~32%

259   of the global ocean (clockwise over the tropical Pacific and tropical Atlantic, and

260   anti-clockwise elsewhere). Consult the Supplementary Information (Figs. S21-

261   S22) for further discussion on the projected future seasonal changes. The results

262   described are mechanistically linked to well-documented large-scale atmospheric

263   wind circulation changes[48,49] and modes of natural climate variability[23].

264   Beyond evaluating the robustness of the projected changes (Fig. 2), we assess

265   the importance of the changes relative to the magnitude of the present-time

266   inter-annual variability (see Supplementary Fig. S20). For RCP4.5, and we

267   speculate the same for lower pathways[51], most robust projected changes in wave

268   parameters fall within the range of present natural variability (<100%). Under

269   the high-emission RCP8.5 however, nearly all robust changes exceed the

270   simulated present-day inter-annual variability (some regions >150%).

271   Fig. 3 identifies robust projected changes in offshore multivariate wave

272   conditions (H_s, T_m and θ_m) in the vicinity of the world's coastlines (Methods

273   Section 6), which are considered dominant physical drivers of coastal

274   change[5,6,13,52] and have served as a proxy for broad-scale assessments of coastal

275   risk and vulnerability[26,35,36,53]. We find ~50% of the world's coasts (excluding sea-

276   ice areas and enclosed-basins) exhibit robust projected changes in the adjacent

277   offshore wave climate in at least one variable ($\acute{H}_s$, $\acute{T}_m$ or $\acute{\theta}_m$). Whilst there are

278   regions where robust projections are limited to a single variable (e.g., $\acute{\theta}_m$

279   changes off the southern and eastern coasts of Africa), there are several coastal

280   sections (~40% of the global coastline) where robust changes in offshore $\acute{H}_s$, $\acute{T}_m$

281   and/or $\acute{\theta}_m$ coincide (e.g., New Zealand, Southern Australia and the western

282   coasts of Central and South America). This is also the case for the highly

283   populated North American Atlantic coast (a well-documented hotspot of

284 accelerated sea-level rise[54], where we find a robust decrease in $\dot{H}_s$ and $\dot{T}_m$.

285 Future projected changes in $\dot{\theta}_m$ (a key driver of sustained coastal erosion[55]) are

286 robust in the vicinity of 21% of the word's coastlines with magnitudes ranging

287 between $\sim\pm17°$. We exclude sea-ice affected regions from our analysis.

288 However, these areas must be acknowledge as locations of potential high future

289 wave climate change, owing to altered wind and fetch conditions with changing

290 sea-ice extent[29,56].

291 Our community-ensemble of global wave-climate projections has a range of

292 uncertainty stemming from several different sources (RCPs, GCMs and WMMs),

293 which have remained largely unquantified in previous, standalone studies. We

294 applied Ward's ANOVA-based clustering (Methods, Section 3.2) to a designed

295 subset of projection scenarios (Table S3) spanning 2 RCP emissions scenarios, 10

296 GCM models and 8 WMMs, providing an overall analysis of similarity amongst the

297 projected changes (Fig. 4). We find that projected relative changes in $\dot{H}_s$ largely

298 cluster by GCM-forcing (i.e., the atmospheric forcing from which the wave field

299 originates). There are only a few cases, where RCP/WMM-related uncertainties

300 dominate the dissimilarity between projections (e.g. MIROC5, BCC-CSM1.1 or

301 CNRM-CM5-forced members). See the Supplementary Information (Section 6.3)

302 for further discussion on the distinctive qualities of each cluster (Section 6.3).

303 To further quantify the dominant drivers of uncertainty among these global

304 wave climate projections and their relative contribution to the total projection

305 uncertainty, we applied a three-factor ANOVA-based variance decomposition to

306 three opportunity subsets (Table S4) containing all three sources of uncertainty.

307 See the Methods (Section 4) for a description of the selection of the subsets used

308 and the ANOVA methodology. The findings show that no single source of

309 uncertainty is negligible, and that the full projection uncertainty is not solely

310 attributable to the different sources of uncertainty, but also depends on their

311 interactions. For all subsets available (Fig. 5, Supplementary Figs. S27-S28) we

312 find a dominating influence of GCM uncertainty across most of the global ocean,

313 accounting for $\sim$30% to more than 50% of the total uncertainty associated with

314 projected future changes in the climatological mean $\dot{H}_s$. These results are

315 consistent with our cluster analysis (cf. Fig. 4).

316 Scenario-driven uncertainty dominates over the North Atlantic, western North

317 Pacific and Southern Ocean ($\sim$40% to more than 50% of the full uncertainty) but

318 is exceeded by other uncertainty contributors elsewhere. Choice of WMMs is a

319 significant contributor to the full uncertainty, particularly across the

320 tropics/subtropics ($\sim$25-50%), and the interactions between uncertainty sources

321 account for $\sim$20-$\sim$30% of the total uncertainty across most of the world's oceans

322 (dominated by GCM-WMM interactions, Fig. 5e). These findings show that all the

323 three sources of uncertainty must be adequately sampled to capture the full

324 uncertainty in the projected change signal. It also demonstrates that previous

325 studies relying on a single methodology have not captured up to ~40-50% of the
326 total uncertainty space (that is, the sum of all the fractions related to WMM).
327 Our global-scale study does not resolve the uncertainty in projections of wave
328 fields introduced with atmospheric downscaling techniques. Although the
329 regional downscaling step has been widely used in wave climate projection
330 studies, and is a topic of intensive research[57], the several different downscaling
331 techniques introduce an additional source of uncertainty which (at present) is not
332 possible to sample at the global-ocean scale.
333 Our CMIP5-based coordinated ensemble of wave-climate projections samples
334 over RCP, GCM and WMMs, thus allowing a much improved sampling of the
335 uncertainty space relative to the COWCLIP CMIP3-based ensemble of
336 opportunity[23], or any previous study to date[21]. In addition to resolving the largely
337 unquantified contribution of all three dominant sources of uncertainty, this study
338 attests to the importance of considering conceptually distinct wind-wave
339 methodologies. We note that, some of the uncertainty seen amongst dynamical
340 simulations in terms of H_s biases could be potentially reduced by further model
341 calibration[58,59] and improved wind-wave model physics (e.g., removing
342 dependence on spectral model approximations, such as for nonlinear wave-wave
343 interactions[60] and model limiters for spectral propagation velocities, applied to
344 improve computational efficiency and accuracy[61,62]). While, at the moment, it is
345 not possible to isolate these components, we advocate that future dynamical
346 wave studies attempt to reduce the overall H_s historical bias. Regarding model
347 skill, wind forcing correction could lead to improved wave model simulations[59].
348 The results also stress the need to better understand how different global wave
349 reanalysis and hindcasts (used to develop historical trends of wave climate
350 change[1,63]) differ.
351 Our results provide a new perspective on the robustness of multivariate global-
352 scale wave projections which builds far beyond the restricted range of future
353 wave-climate scenarios published in individual studies to date. These
354 coordinated ensemble projections show signals of wave climate change will not
355 exceed the magnitude of the natural climate variability if the goal of the Paris
356 Agreement 2° C degree target is kept. Under a high-emission scenario (RCP8.5),
357 ~48% of the world's coast is at risk of wave climate change, owing to changes in
358 offshore forcing $\acute{H}_s$, $\acute{T}_m$ and/or $\acute{\theta}_m$ (with ~40% exhibiting robust changes in at
359 least two of these wave variables). The magnitude of the future projected
360 changes found for any of these wave variables (~5-15%) is capable of inducing
361 significant changes in coastal wave-driven processes and their associated
362 hazards[52].
363 Broad-scale assessments of coastal impacts of climate change are beginning to
364 consider changes to wave climate[1,35,36,53] however, these studies are yet to
365 consider directional shifts in wave propagation, which have been shown to be a

366 dominant driver of shoreline stability[5,13]. Whilst our results have far-reaching
367 implications from many perspectives, they only address meteorologically-driven
368 changes in wind-wave characteristics, which have been the predominant focus of
369 wind-wave climate projection studies to date. Some localised-scale studies
370 suggest the morphologically-driven component of wave climate change might
371 lead to a greater change in the coastal zone than these meteorologically-driven
372 changes[11]. Concentrated community effort is now required to quantify
373 morphologically-driven wave climate change as a contributor to global coastal
374 water-level changes, as we look towards improved coastal vulnerability
375 assessments from the climate community[64].
376
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584

585   **List of Figure captions**

586

587   **Fig. 1** - **Hierarchical clustering of annual mean significant wave height (**
588       $\acute{H}_s$**) for the present-day climate (1979-2004). a,** Cluster tree diagram
589   (dendrogram) resulting from Euclidean distance-based Ward's minimum variance
590   (Methods, Section 3) clustering using global pairwise annual $\acute{H}_s$ (Methods). The
591   vertical axis represents the distance or dissimilarity between clusters (and
592   cluster members) presented in log-scale for clarity. In the horizontal axis, the
593   members are labelled by model forcing (GCM) and wind-wave modelling method
594   (WMM) (coloured accordingly). The multi-model ensemble mean from each WMM
595   is also included with its respective colour. Full multi-member ensemble averages
596   (weighted ensemble mean by WMM, ENSEMBLE-WM, and uniformly weighted
597   ensemble mean, ENSEMBLE) are coloured blue (Methods, Section 3.1). Grey
598   shading denotes five well-defined key clusters. **b,** Within each dashed line
599   section, maps showing the of each cluster in terms of absolute value (top row)
600   and relative percentage difference to the satellite database (bottom row) are
601   shown for annual $\acute{H}_s$ (Methods, Section 3.1). The numbers at the bottom left of
602   each panel are the number of cluster members used to calculate the cluster
603   mean.

604

605   **Fig. 2 - Simulated wave climatological mean fields for the present-day**
606   **(1979-2004) and projected changes in the climatological wave values by**
607   **the future period 2081-2100 under RCP4.5 and RCP8.5. a,** The weighted
608   multi-member mean of the 1979-2004 mean of annual mean significant wave
609   height $\acute{H}_s$, (December-February DJF and June-August JJA $\acute{H}_s$ within dashed box
610   with same colorbar as for annual $\acute{H}_s$), 99th percentile significant wave height, H_s^{99},
611   mean wave period, $\acute{T}_m$, and mean wave direction, $\acute{\theta}_m$. **b-c,** The weighted multi-

612 member mean of projected changes in the climatological mean of the respective
613 wave parameter by the period 2081-2100 relative to the period 1979-2004 under
614 RCP4.5 and RCP8.5, respectively. The changes are expressed in percent of the
615 present-day climatological values. Changes in $\acute{\theta}_m$ (clockwise) are absolute
616 changes with vector direction denoting $\acute{\theta}_m$ for the present-day climatological
617 mean field. Hatching indicates areas of robust change (Methods, Section 5).
618 Seasonal changes for each wave parameter are provided in Supplementary Figs.
619 S21-S22.

620

621 **Fig. 3 - Robust projected changes in offshore significant wave height ($\acute{H}_s$**
622 **), period ($\acute{T}_m$) and direction ($\acute{\theta}_m$) by 2080-2100 (under RCP8.5) in the**
623 **vicinity of the world's coastlines.** Sections exhibiting robust weighted multi-
624 member mean changes under RCP8.5 are coloured according to the qualitative
625 colourbar (bottom), which also shows the percentage of affected coastline where
626 changes are robust (Methods, Section 5) for each wave characteristic(s). Regions
627 exhibiting a simultaneous robust increase in offshore $\acute{H}_s$ and robust decrease in
628 offshore $\acute{T}_m$ (or vice versa) are extremely limited. Vectors represent robust
629 projected changes in offshore $\acute{\theta}_m$ with their angle (° North) representing wave
630 direction over the historical time-slice (1979-2004) and their color representing
631 the magnitude of the future changes (according to the quantitative colourbar,
632 right side). The percentage of affected free-ice coastline with robust changes in
633 offshore $\acute{\theta}_m$ is estimated at ~21% (Supplementary Table S2). Coastlines without
634 black outline represent sea-ice areas and enclosed seas excluded from analysis
635 (Methods, Section 6).

636

637 **Fig. 4** - **Hierarchical clustering of projected relative changes in annual**
638 **mean significant wave height ($\acute{H}_s$) (2081-2100 relative to 1979-2004). a,**
639 Cluster tree diagram resulting from Euclidean distance-based Ward's minimum
640 variance clustering using global pairwise projected change annual $\acute{H}_s$ (Methods,
641 Section 3). The vertical axis represents the distance or dissimilarity between
642 clusters (and cluster members) presented in log-scale for clarity. In the
643 horizontal axis, the members are labelled by GCM forcing, WMM and RCP
644 scenario (RCP4.5 simulations are italicized) respectively, and coloured by GCM,
645 accordingly. The multi-model ensemble mean from each study group is also
646 included. Full multi-member ensemble averages (weighted ensemble mean
647 weighted by WMM, ENSEMBLE-WM, uniformly weighted ensemble mean,
648 ENSEMBLE, and ensemble mean weighted by forcing, ENSEMBLE-WF) are
649 coloured blue (Methods, Section 3.2). Grey shading denotes five well-defined key
650 clusters. **b,** Within each dashed line section, maps showing the mean of each
651 cluster's projected relative change in annual $\acute{H}_s$ (m) is shown (Methods, Section

652   3.2). The numbers at the bottom left of each panel are the number of cluster
653   members used to calculate the cluster mean.
654

655   **Fig. 5 - Relative contribution of different sources of uncertainty to the**
656   **projected future changes in the mean of annual/seasonal significant**
657   **wave height ($\acute{H}_s$). a-d**, Fraction of the total uncertainty (variance) in the
658 projected $\acute{H}_s$ changes (2081-2100 relative to 1979-2004) attributable to **a)** global
659   climate models (GCMs), **b)** wind-wave modelling methods (WMMs), **c)**
660   representative concentration pathways (RCPs) and **d)** sum of all interaction
661   terms. **e)** Spatially-averaged contribution of each uncertainty source and their
662   pairwise and triple interactions to the total ensemble uncertainty. Results are
663   derived from the ensemble subset 2 which consist of 6 GCMs, 2 RCPs and 3
664 WMMs for a total of $N = 36$ simulations (Supplementary Table S4). Similar results
665   are found for subset 1 and 3 and are presented in Supplementary Fig. S16-S17.
666 The variance partitioning is based on a three-factor ANOVA model complemented
667   with a subsampling scheme (Methods, Section 6). Note that plotting artifacts
668   such as horizontal lines reflect the effects of the spatial-domain partitioning
669   applied in the statistical methodologies.
670 **Methods.**
671 **1. Data contribution**
672   We use a community-derived ensemble compiled from ten CMIP5-based global
673 wind-wave climate projection studies[25-34], completed under a pre-designed
674 framework[41,42]. Annual and seasonal means of significant wave height (H_s), mean
675 wave period (T_m), mean wave direction (θ_m) as well as 10th/99th percentiles of
676 annual/seasonal H_s are obtained from the ten individual studies. Consult
677 Supplementary Information for a detailed description of the datasets considered
678 and framework.
679   Our analysis assesses projected relative changes between the representative
680 present-day (1979-2004) and future (2081-2100) time-slices. These time periods
681 align with the CMIP5 GCM archives of high-temporal resolution atmospheric fields
682 used to develop wind-wave projections; and correspond to the common period
683 across nine of the ten contributing datasets (see Supplementary Section 1.1
684 Table S1). Contributed datasets are considered under two different greenhouse-
685 gas representative concentration pathways: RCP4.5 and RCP8.5 describing
686 medium-stabilizing and high-radiative forcing scenarios - reaching +4.5 W/m^2
687 and +8.5 W/m^2 (relative to pre-industrial 1850-conditions) respectively. Sea-ice
688 regions were excluded from analysis to support inter-comparison between the
689 different contributions.
690

691 **2. Skill of GCM-forced wave climate simulations**

692   As previously mentioned, all contributing studies[25-34] have provided
693   assessments of the skill of their GCM-forced global wind-wave simulations to
694   represent the historical wave climate on an independent basis. Here we use two
695   historical wave datasets (a recently compiled dataset of altimeter measurement
696   records and a well-known global wave reanalysis) exclusively as a common point
697   of reference for our model ensemble inter-comparison. The two datasets are
698   briefly described below.
699
700   **2.1 Historical satellite altimeter measurements**
701   We compare the GCM-forced wave simulations with the most recent (and
702   complete) database[43] of satellite H_s measurements. This database combines 13
703   radar altimeters which have been extensively calibrated against the National
704   Oceanographic Data Center (NODC) buoy data, and cross-validated against an
705   independent compiled buoy dataset supplied by the ECMWF[43,65]. The dataset
706   contains H_s on a 2° grid resolution (at global scale) over a period of 33 years
707   (1985-2018). After control analysis, we found partial years over 1985-1989
708   (when only GEOSAT data is available) and no data available for 1991 which limits
709   the data to 1992-2018, providing a common time-slice duration for comparison
710   of 26 years.
711   In the comparison of the GCM-forced global wave simulations with the altimeter
712   measurements, the time-slice mismatch is ignored[66]. Since the GCM atmospheric
713   forcing (and the spectral wave models) were not subject to any data assimilation,
714   they are considered as representative of the historical wave climate regardless
715   of the time period[66]. Note that GCM simulations (and their natural internal
716   climate variability and its associated large-scale modes) are not in temporal
717   phase with the satellite database. We assume that any differences between
718   GCMs and altimeter measurements are attributable to model and observation
719   biases and not from the non-stationarity of the wind-wave climate[23].
720   To allow for intercomparison, the wave parameters obtained from each of the
721   contributions[25-34] were collocated onto the satellite-database global grid
722   preserving the original data. Taylor diagrams[46] were used to compare the skill of
723   the GCM-forced wave simulations to represent the present H_s climate at both
724   global and regional-scale (Supplementary Figs. S1-S3 and Figs. S4-S5
725   respectively). We clarify that our Taylor diagrams present a spatial pattern
726   correlation of a temporal average (and not a spatio-temporal correlation). In
727   addition to Taylor diagrams, we present global pairwise comparisons maps of the
728   mean and variability H_s biases for a subset from the full ensemble with common
729   GCM-WMM (Supplementary Table S3), allowing us to identify the spatial
730   variations of the biases (Supplementary Figs. S12-S13, S16-S17, respectively).
731
732   **2.2 ERA-Interim wave reanalysis**

733   In addition to the univariate satellite data[45] we compare model-skill over the
734   present-day wave climate (1979-2004), by comparing the present-day GCM-
735   forced global wave simulations with the wind-wave parameters obtained from
736   the observationally constrained ECMWF ERA-Interim[45] (ERAI) global wave
737   reanalysis. The ERAI is a consistent spatially and temporally complete dataset[45],
738   which has been widely used[1,25,67] and extensively validated[44] being considered
739   appropriate for multi-year analysis and modeling of long-term processes[44]. The
740   ERAI database provides 6-hourly values of H_s, T_m and θ_m on a 1° global
741   resolution, allowing us to compare all wave variables of interest at global-scale.
742   The ERAI is therefore used as a well-known reference database, allowing us to
743   compare all contributing simulations under the same reference.
744   We note that, despite its relatively good model-skill against buoy and altimetry
745   measurements[44], the ERAI still exhibits some biases in the H_s upper percentiles
746   (95th and above), where it underestimates altimetry measurements of H_s by
747   ~10-15%[44].
748   The original 6-hourly multivariate ERAI dataset was used to calculate a
749   standard set of statistics as performed for the contributing studies[25-34] (see
750   Supplementary Information, Section 2). To allow for intercomparison, the surface
751   wave parameters derived from each of the contributing studies[25-34] were
752   bilinearly interpolated onto the ERAI grid. Taylor diagrams[46] were adopted as a
753   representation of the skill of the GCM-forced wave simulations to reproduce the
754   present multivariate wave climate (H_s, T_m and θ_m) at both global and regional-
755   scale (Supplementary Figs. S6-S8 and Fig. S9, respectively). The global pairwise
756   comparison maps of mean and variability bias using the ERAI dataset are
757   presented in Supplementary (Figs. S14-S14 and Figs. S18-S19).
758
759   **3. Cluster methodology**
760   We applied an agglomerative-hierarchical clustering analysis, with the
761   similarity criterion defined by Ward's ANOVA-based minimum variance
762   algorithm[68]. The clustering method was used without
763   imposing any restrictions on the number and size, or a priori assumptions, of
764   clusters. Initial cluster distances were derived using a multi-dimensional
765   approach, where the pair-wise Euclidean distance ($D_{\dot{\iota}}$ amongst ensemble
766   members are calculated at every grid location rather than spatially-averaged,
767   hence clustering members with high similarity in terms of spatial pattern and
768   magnitude:
769

770
$$D_{i,j,k} = \sqrt{\sum_{k=1}^{w} \left(x_{i,k} - x_{j,k} \right)^2} \qquad (1)$$

771

772 where $x_{i,k}$ and $x_{j,k}$ are the magnitudes of the relative projected change in the
773 annual mean significant wave height from the GCMs i and j respectively, at grid
774 point k, with w equal to the number of ocean grid points. Note that for the
775 clustering of present-day wave simulations we have used absolute values rather
776 than relative changes. The usage of annual mean significant wave height ($\acute{H}_s$) as
777 our clustering variable is based on the fact that $\acute{H}_s$ is the only parameter
778 available from all the contributions and our main objective is to analyse the total
779 community ensemble of wave simulations. Note that, statistical-method-derived
780 members[33,34] from ECCC (s) and IHC did not provide wave period and/or
781 directions (Supplementary Table S1). We also carried out a multivariate
782 clustering based on annual $\acute{H}_s$, $\acute{T}_m$ and $\acute{\theta}_m$ (not shown) using our dynamical
783 subset of simulations, which showed qualitatively similar results to the $\acute{H}_s$-based
784 clustering, in both the present-day simulations and projected relative changes.
785 Further description of the clustering method application to the present-day
786 climate and the projected relative changes is provided below.
787
788 **3.1 Application to present-day simulations**
789   Annual $\acute{H}_s$ from each GCM-forced global wave simulation over the present-day
790 time-slice (1979 to 2004) was used in the clustering method (Eq. 1). We included
791 all existing ensemble models as well as the mean of each individual contributing
792 study ensemble, a uniformly weighted ensemble mean (i.e., attributing equal
793 weight to individual member) and an ensemble mean weighted by WMM. The
794 latter consisted of reducing the full ensemble to n-members with each single
795 member representing the mean from a specific WMM (when suitable). For
796 example the 30-model IHC ensemble was reduced to one member, representing
797 its ensemble mean. The relative differences (%) between the average of all the
798 members within each main cluster and the satellite data was calculated
799 separately for each parameter, simply to highlight the key qualities of each
800 cluster (Fig. 1 and Supplementary Fig. S10). The relative difference was also
801 calculated using ERAI (Supplementary Fig. S11). Note that the clustering analysis
802 (Fig. 1) is fully independent from the comparison with the satellite or the ERAI
803 datasets as described in Section 3.
804   We applied the clustering analysis to annual and seasonal $\acute{H}_s$ values combined,
805 and the results were consistent with those obtained using annual mean values.
806 We also applied the clustering procedure to the other wave parameters
807 (individually), and obtained consistent findings. In all cases, the present-day
808 simulations are strongly dependent on the WMM adopted by each study group to
809 develop future wave fields as shown in Fig. 1.
810
811 **3.2 Application to projected future changes**

812   To identify and resolve similarities in the projected future change the
813   clustering procedure (Eq. 1) was applied to the projected relative changes in
814   annual $\acute{H}_s$ between the present-day (1979-2004) and future (2081-2100) time-
815   slices as estimated by each of the GCM-forced global wave simulations:
816

817    $$\Delta H_{j,k} = \frac{\acute{H}_{j,k}^{Future} - \acute{H}_{j,k}^{Present-day}}{\acute{H}_{j,k}^{Present-day}} \qquad (2)$$

818   where $\Delta H_{j,k}$ is the projected change by GCM j at each grid node k.
819   To resolve the relative importance of the three different sources of uncertainty
820   (i.e. RCP scenarios, GCMs, and WMMs), we use a subset from the full community
821   ensemble where each member shares common GCM forcing with at least two
822   other members obtained from different WMMs (consult the Supplementary Table
823   S2). In the clustering of projected relative changes (Eq. 1), we also included the
824   mean of each study contribution, the uniformly weighted ensemble mean
825   (Section 3.1), the ensemble mean weighted by GCM (section 5) and the
826   ensemble mean weighted by WMM (for each RCP). Five key clusters were
827   identified based on the clustering results as an indication of ensemble members
828   with considerable dissimilarity in the projected change values. The mean of all
829   members within each main cluster (when available) was calculated for each
830   wave parameter (Fig. 1 and Supplementary Fig. S25), providing a robust
831   indication of spatial and magnitude dissimilarities over the global ocean.
832   For completeness, we also applied the cluster analysis to the entire community
833   ensemble of global wind-wave projections, yielding consistent dissimilarities and
834   respective associations between all the available wave simulations (albeit less
835   clear owing to the large size of the ensemble) (Fig. S26).
836
837   **4. ANOVA methodology**
838   **4.1 Approach and selection of subsets**
839   Uncertainty in the projected future wave climate changes (2081-2100 relative
840   to 1979-2004) within our community-based multi-member ensemble arises from
841   three different sources: choice of emission scenarios (RCPs), global climate
842   models (GCMs), and wind-wave modelling methods (WMMs). The latter refers to
843   the different statistical and dynamical wave modelling approaches used to
844   simulate the global wind-wave fields (representing different configurations of
845   statistical methods - such as transfer functions, training data sets and/or
846   predictor corrections, and/or dynamical wave models including the source-term
847   packages, sea-ice forcing and numerical model resolution). In contrast with other
848   climatic variables (e.g., temperature or precipitation), dynamically-derived
849   ensembles of wave projections are typically only available for 20-year period,
850   constrained by the availability of high-temporal resolution GCM-simulated

851 atmospheric surface winds[21,42] (Supplementary Table S2). This constrains testing
852 the projection uncertainty against the natural (temporal) variability.
853   Hence, we decompose the total ensemble uncertainty in the projected changes
854 in the long-term (20-year) mean of annual/seasonal $\acute{H}_s$ into contributions from
855 the different sources of uncertainty (RCPs, GCMs and WMMs) and the
856 interactions between them. The fraction of the uncertainty attributable to each
857 source (at each grid node) is determined using a three-factor ANOVA[69]-based
858 variance partition method (Section 4.3). The method was applied separately to
859 three opportunity subsets obtained from the full ensemble, with each subset
860 containing all three sources of uncertainty (Supplementary Table S3). No other
861 subsets with the same number of factors exist in this community ensemble. Note
862 that the forcing GCMs within subsets 2 and 3 represent a broad cross-section of
863 the CMIP5 ensemble[49], particularly that with availability of high-temporal
864 resolution surface wind fields, in terms of model components[70] and various GCM
865 characteristics such as spatial resolution[70].
866
4.2 Subsampling scheme
868   The ANOVA-based variance decomposition using different sample sizes of
869 variance sources result in biased variance estimators[71] (cf. Fig. 4 and
870 Supplementary Fig. S27-S28 with Supplementary Fig. S29). To reduce such
871 biases in the estimates of variance for quantification of the uncertainty
872 contribution, we complemented the ANOVA based variance decomposition with a
873 subsampling methodology previously proposed[71]. In each subsampling iteration i,
874 we select two out of n-climate models and two out of m-wave models,
875 representing a total of $C_2^n C_2^m$ subsamples, with n and m denoting the number of
876 GCMs and WMMs within each subset respectively. For each subsample iteration i,
877 we end up with two global climate models, two emission scenarios and two wind-
878 wave-modelling approaches, which we used for variance decomposition as
879 described below.
880
4.3 Three-factor ANOVA model based variance decomposition
882   Letting Y_{jkl}^i be our response variable, representing the projected change in $\acute{H}_s$
883 from the jth GCM, kth RCP and lth WMM, we define our three-factor ANOVA-based
884 partition model[71] without replication following[71,72]:
885

$$Y_{jkl}^i = \mu^i + \alpha_j^i + \beta_k^i + \gamma_l^i + (\alpha\beta)_{jk}^i + (\alpha\gamma)_{jl}^i + (\beta\gamma)_{kl}^i + \delta_{jkl}^i \qquad (3)$$

887

888 where μ^i is the grand-mean projected change of the subsample i. The terms α_j^i,
889 β_k^i, and γ_l^i represent the variance arising solely from the factors GCMs, WMMs,
890 and RCPs (respectively), with j, k and l denoting samples of the different factors

891   ($j = 1,2$; $k = 1,2$; and $l = 1,2$) for each subset of simulations by a combination of
892   two GCMs and two WMMs for two RCPs. The three terms $(\alpha\beta)^i_{jk}$, $¿$, and $(\beta\gamma)^i_{kl}$
893   represent the interactions between the specified pair of factors (i.e. 2-factor
894   interaction terms). The term δ^i_{jkl} represents the variance arising from the 3-factor
895   interactions $(\alpha\beta\gamma)^i_{jkl}$, and the internal variability. Note that here the natural
896   internal variability is negligible as we are analysing differences between two
897   climatological mean values, that is involving very little temporal variance. There
898   are no replications for estimating the internal variability. Therefore, we cannot
899   and did not test the statistical significance of variance arising solely from each
900   factor against the natural variability, and thus did not require any assumptions
901   for the residuals of model. The results derived from each subsample i are the
902   unbiased estimates of fraction of the total uncertainty attributable to each
903   source[71,73] with the variance fraction η^2 for each factor derived as:
904

905 $$\eta^2_{GCM} = \frac{1}{I}\sum_{i=1}^{I}\frac{SS\alpha_i}{SST_i}, \tag{4}$$

906 $$\eta^2_{WMM} = \frac{1}{I}\sum_{i=1}^{I}\frac{SS\beta_i}{SST_i}, \tag{5}$$

907 $$\eta^2_{RCP} = \frac{1}{I}\sum_{i=1}^{I}\frac{SS\gamma_i}{SST_i}, \tag{6}$$

908 $$\eta^2_{GCM-WMM} = \frac{1}{I}\sum_{i=1}^{I}\frac{SS\alpha\gamma_i}{SST_i}, \tag{7}$$

909 $$\eta^2_{GCM-RCP} = \frac{1}{I}\sum_{i=1}^{I}\frac{SS\alpha\gamma_i}{SST_i}, \tag{8}$$

910 $$\eta^2_{RCP-WMM} = \frac{1}{I}\sum_{i=1}^{I}\frac{SS\beta\gamma_i}{SST_i}, \tag{9}$$

911 $$\eta^2_{RCP-GCM-WMM} = \frac{1}{I}\sum_{i=1}^{I}\frac{SS\delta_i}{SST_i}$$

912   (10)

913   Values of 0 and 1 for the variance fraction η^2_x correspond 0% and 100%
914   contribution of factor x to the total ensemble variance (uncertainty),
915   respectively. The average variance fractions are presented in Fig. 5 for each
916   factor and for the sum of all the interaction terms, to compare the relative
917   magnitude of each source of uncertainty. An assessment of the significance of
918   the projected changes relative to the magnitude of the natural internal variability
919   is provided in Supplementary Fig. S20, based on one realisation available for
920   each member (Supplementary Table S1).
921

5. Analysis of projected change

Projected changes in all wave variables (except $\acute{\theta}_m$) between the present and future time-slices were calculated as percentage changes, for each member (from each contribution) directly forced by GCM-simulated surface wind or pressure fields. The LBNL[31] and KU[32] data were derived using downscaled forcing via high-resolution atmospheric models driven by particular SST conditions (Supplementary Section 1.1) and therefore were not included in this analysis.

Projected changes in $\acute{\theta}_m$ were calculated as absolute values and shown as clockwise (anticlockwise) rotation in degrees relative to the present-day climate mean. Projected changes were calculated under RCP4.5/RCP8.5. A weighted multi-member ensemble mean of projected changes was then calculated. Fifty statistical wave projections are available from IHC and ECCC (s) combined (for both scenarios), whilst the dynamical projections consist of 23 (RCP4.5) and 25 (RCP8.5) projected change scenarios, as per Table S1. The projected relative change strongly depend on GCM forcing (atmospheric wind or pressure fields from which the wave field originates from) (Fig. 4 and 5), therefore a weighted multi-member ensemble mean was calculated by applying a weighting factor to each member:

$$\acute{x}_k = \frac{\sum_{i=1}^{n}\left(\Delta_{i,k} \times W_{i,k}\right)}{\sum_{i=1}^{n}\left(W_{i,k}\right)}$$

(11)

where $\Delta_{i,k}$ is the projected change for a given wave parameter k by the ensemble member i and W_i is the weighting factor for the ensemble member i for that same parameter (determined as the number of ensemble members with that same forcing GCM amongst all members n). For all wave parameters, the global map of mean projected change was derived as the n-member ensemble weighted mean difference between projected and present wave-climate fields from Eq. (11).

5.1 Robustness measure

We use a methodology[18] identified by the IPCC AR5 WG1[74] as being a suitable, effective method to identify regions of robustness. In contrast to other criteria, this robustness criteria[18] does not ignore the existence of internal climate variability, and clearly identifies regions with a lack of member agreement and/or lack of climate signal (by assessing the level of consensus on the significance of change as well as the signal of change)[18,75].

959   We assessed the significance of change projected by each of the ensemble
960   members individually, with a two-tailed Welch's *t*-test that allows for different
961   variances between over the present and future time-slices. The test was
962   conducted at 5% significance level. To define areas of robust projected changes
963   we first identified areas (grid points) where 50% or more of the ensemble
964   members projected a significant change. Within these areas, we further
965   identified the areas where 90% or more of the ensemble members exhibiting a
966   significant change agreed on the sign of the projected changes; these are the
967   areas of robust changes projected by the ensemble, and are hatched in Fig. 2.
968   Note that we employed a higher threshold (90%) than the default 80%[18,75] for
969   members' agreement on the sign of the projected changes. The key conclusions
970   are similar if other IPCC-referenced methods were used to measure robustness[74].
971   As a complement to the robustness criteria[18] we further confirmed that, within
972   all regions with robust projected changes, the ensemble mean of projected
973   changes is statistically significantly different from zero (i.e. stands out of the
974   inter-member variability) according to the result of one-sample student *t*-test at
975   5% significance level.
976
977   **6. Percentage of coastline with robust changes in offshore forcing wave**
978   **conditions**
979   In this analysis, we consider all the available offshore deepwater (>~200 m)
980   grid points, distributed along the global coast every ~100 km. The coast is taken
981   from the Global Self-consistent Hierarchical High-resolution Geography
982   database[76]. We limit our analysis to offshore changes owing to the limited ability
983   of the CMIP5 GCMs to adequately capture fetch-limited, near-coastal wind fields
984   and land-sea interactions (e.g., orographic and katabatic effects) given their
985   coarse spatial resolution. Nevertheless, we note that our GCM-forced wave
986   simulations exhibit good agreement against near-coast buoys[30,53], even within
987   semi-enclosed seas (e.g. Mediterranean)[53] and in extreme wave conditions[77]. The
988   model skill reported for near-coast buoys is comparable to that against offshore
989   buoys and to high-resolution coastal wave hindcasts[78]. Sections of coast without
990   available wave model outputs were not considered which included sea-ice areas
991   and enclosed seas.
992
993   **Data Availability**
994   The data that support the findings of this study are available from the
995   corresponding author upon request, or via the COWCLIP data access portal:
996   https://cowclip.org/data-access/.
997
998   **Methods References**
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1049

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1051

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1083
1084 **Authors Contribution**
1085 All authors (except CT, NC, MW, BT and FA) had input into experimental design
1086 via workshop.
1087
1088 JM led analysis of ensemble, algorithm development for data analysis and writing
1089 of manuscript; MH co-led and conceived the experiment, supervised analysis,
1090 provided CSIRO ensemble data, and co-wrote manuscript; XL co-led and
1091 conceived the experiment, developed community codes, provided ECCC
1092 ensemble data, and contributed to analysis and written manuscript; NC
1093 supervised analysis and contributed to written manuscript; CT provided CSIRO
1094 ensemble data, coordinated data, and contributed to written manuscript; IY
1095 provided satellite data, contributed to analysis and written manuscript; AS
1096 provided IHE ensemble data, contributed to analysis and written manuscript. NM
1097 and TS provided KU ensemble data and contributed to written manuscript; LE
1098 provided USGS ensemble data and contributed to written manuscript; OA & OB
1099 contributed ERA-Interim statistics; MD, AB & JoS contributed IHE ensemble data;
1100 LM contributed JRC ensemble data and developed community codes; MC-P
1101 contributed ECCC ensemble data and contributed to written manuscript; PC &
1102 MM contributed IHC ensemble data and contributed to written manuscript; BT
1103 and MW contributed LBNL ensemble data and contributed to written manuscript;
1104 LB and JW contributed NOC ensemble data; AW and BK had input via workshop;
1105 JuS contributed to analysis and written manuscript; FA assisted with figure
1106 development.