Title

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Journal

Nature Climate Change, 9(9)

ISSN

1758-678X

Authors

Morim, Joao
Hemer, Mark
Wang, Xiaolan L
et al.

Publication Date

2019-09-01

DOI

10.1038/s41558-019-0542-5

Peer reviewed

Robustness and uncertainties in global multivariate wind-wave climate projections

Joao Morim*[,1,2,3], Mark Hemer[3], Xiaolan L. Wang[4], Nick Cartwright[1], Claire Trenham[3], Alvaro Semedo[5,6], Ian Young[7], Lucy Bricheno[8], Paula Camus[9], Mercè Casas-Prat[4], Li Erikson[3], Lorenzo Mentaschi[10], Nobuhito Mori[11], Tomoya Shimura[11], Ben Timmermans[12], Ole Aarnes[13], Øyvind Breivik[13,14], Arno Behrens[15], Mikhail Dobrynin[16], Melisa Menendez[9], Joanna Staneva[15], Michael Wehner[17], Judith Wolf[8], Bahareh Kamranzad[18], Adrean Webb[11], Justin Stopa[19], Fernando Andutta[1].

[1]School of Built Environment and Engineering, Griffith University, Southport, Queensland, Australia.
[2]Commonwealth Scientific and Industrial Research Organisation (CSIRO) Oceans and Atmosphere, Hobart, Tasmania, Australia.
[3]US Geological Survey (USGS), Pacific Coastal and Marine Science Center, Santa Cruz, CA, USA.
[4]Environment and Climate Change Canada, Climate Research Division, Toronto, Ontario, Canada.
[5]IHE-Delft, Department of Water Science and Engineering, Delft, The Netherlands.
[6]Instituto Dom Luiz, Faculty of Sciences of the University of Lisbon, Lisbon, Portugal.
[7]Department of Infrastructure Engineering, University of Melbourne, Parkville, Victoria, Australia.
[8]National Oceanographic Centre, Liverpool, United Kingdom.
[9]Environmental Hydraulics Institute (IHCantabria), Universidad de Cantabria, Santander, Spain.
[10]European Commission, Joint Research Centre (JRC), Ispra, Italy
[11]Disaster Prevention Research Institute, Kyoto University, Kyoto, Japan.
[12]Climate and Ecosystems Science Division, Lawrence Berkeley National Laboratory (LBNL), Berkeley, California, USA.
[13]Norwegian Meteorological Institute, Bergen, Norway.
[14]Geophysical Institute, University of Bergen, Bergen, Norway.
[15]Helmholtz-Zentrum Geesthacht Centre for Materials and Coastal Research, Geesthacht, Germany.
[16]Institute of Oceanography, Center for Earth System Research and Sustainability (CEN), Universität Hamburg, Hamburg, Germany.
[17]Computational Research Division, Lawrence Berkeley National Laboratory (LBNL), Berkeley, California, USA.

[18]Graduate School of Advanced Integrated Studies in Human Survivability/Hakubi Center for Advanced Research, Kyoto University, Japan.
[19]Department of Ocean and Resources Engineering, University of Hawaiʻi at Mānoa, Honolulu, Hawaii, USA.

*Corresponding author address:
Eng. Joao Morim
School of Built Environment and Engineering (G39),
+61424467749, Griffith University,
Gold Coast, Southport 4222 QLD, Australia
Email: joao.morimnascimento@griffithuni.edu.au

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 assessing regions with lack of climate signal and/or inter-member agreement) (see Methods section 5)[18] and quantifying the uncertainties introduced by the complex modelling processes used for that purpose, is paramount to prevent potentially costly maladaptation[19,20]. A problem, however, arises from the wide range of wind-wave methodologies used to derive wave characteristics from surface winds or pressure fields, which increases the poorly-understood uncertainty in existing projections[21-23]. Consequently, the the United Nations Intergovernmental Panel on Climate Change (herein IPCC) Fifth Assessment Report (AR5)[24] assigned low confidence to wave projections (with medium confidence for Southern Ocean H_s increase), owing to the limited number of available model simulations and the uncertainty surrounding Global Climate Model (GCM) downscaled surface winds.

Since then, a new generation of global wind-wave projection studies have been completed by several international modelling groups[25-34] using atmospheric forcing fields obtained from the Coupled Model Intercomparison Project Phase 5 (CMIP5) GCM simulations. While each of these independent studies has considered aspects of the uncertainty related to their own specific climate-modelling process, they treated the uncertainty space very differently (such as emission scenarios and/or GCMs). Furthermore, no studies quantified the uncertainty introduced by their own particular wind-wave modelling method (WMM) to develop global wind-wave fields. This uncertainty stems from different configurations of statistical approaches (including transfer functions, training datasets and predictor corrections) and/or dynamical wind-wave models (including source-term parameterizations, sea-ice fields and numerical resolution) (Supplementary Table S1).

Consequently, these studies present contrasting projected changes in wind-wave characteristics (in terms of magnitude and/or signal) across the world's ocean[21]. Such limitations might have potentially hampered broad-scale assessments of future coastal risk and vulnerability[1,22]. These assessments have either used future H_s changes derived from a very limited number of GCM-forced global wind-wave simulations surrounded by low confidence[35,36], or have neglected any future wave changes[37,38] on the basis of the unavailability of robust global data[39] and the high uncertainty between existing studies[40].

Here, we seek to minimize such limitations by performing a unique analysis of a coordinated multi-method ensemble of future global wave climate scenarios derived from ten independent state-of-the-art studies[25-34]; which have been undertaken under a pre-designed, community-driven framework[41,42]. Combined, these studies yield a large ensemble of 148 members of global wave-climate projections, from which we identify robust projected meteorologically-driven changes in H_s, T_m and θ_m at global scale. Further, this multi-method ensemble of wave projections enables us to quantify (and compare), for the first time, all three dominant sources of uncertainty (emission scenarios, global climate models and wind-wave modelling methods); which has not been previously attempted owing to lack of multi-method ensembles.

Two[33,34] of the ten contributing studies employ different statistical approaches to derive global wave projections exploiting relationships between GCM-simulated sea-level pressure (SLP) fields and wave parameters. The remaining contributions[25-32] use different configurations of dynamical approaches, in which GCM-simulated high-temporal resolution near-surface winds are directly used to drive a global wind-wave model. Consult the Supplementary Information (Section 1.1, and Table S1) for the details of each contribution and respective acronyms.

All the contributing studies[25-34] have provided assessments of the performance of their GCM-forced wave simulations to represent the historical wave climate on an independent basis. Here, we compare the model-skill of each ensemble member, against the most recent and complete, calibrated dataset of satellite altimeter $H_s$measurements of H_s[43]. In addition, we compare the model-skill against the well-validated[44] ERA-Interim[45] (ERAI) multivariate (H_s, T_m, θ_m) wave reanalysis for the present-day time-slice (1979-2004) as a common reference dataset. The details of the two databases are described in the Methods (Section 2). We present our model-skill comparisons using Taylor diagrams[46] at both global- and regional-scale, providing spatial correlation (SC), normalized standard deviation (NSD) as well as centred-root-mean-square-difference (CRMSD) within a single diagram. To further support our model skill analysis, we provide global pairwise comparisons maps of the mean and variability biases for a subset with common forcing GCM-WMM (Supplementary Table S3, Section 5).

Overall, both dynamical and statistical-based simulations exhibit good agreement relative to satellite measurements and ERAI. CRMSD values in annual/seasonal $\acute{H}_s$ are generally below 0.5 m, with NSD values below 0.5 m and SC values above 0.9 at global- and regional-scales, regardless of the reference dataset used here (Supplementary Figs. S1-S4, S6-S8). The agreement in annual mean 99th percentile significant wave height (H_s^{99}) is relatively similar to that seen for $\acute{H}_s$. However, we find relatively less model-skill in representing annual H_s^{99} at regional-scale, particularly across the South Atlantic/Pacific and Southern Indian Ocean with NSD values up to ~1 m (Supplementary Fig. S5). The bias values in annual $\acute{H}_s$ and H_s^{99} relative to satellite data are usually under ~10-15% and ~15-17.5% over the global ocean, respectively (Supplementary Figs. S12-S13). The ensemble mean of each study exhibits biases of less than ~5% in annual $\acute{H}_s$ anywhere, respectively. Comparison against the ERAI data in terms of annual/seasonal $\acute{T}_m$ and $\acute{\theta}_m$ exhibits good agreement, with the CRMSD values under 0.5 s and 0.75°, respectively, and SC values above 0.9 (Supplementary Figs. S6-S8), at both global and regional-scale (Supplementary Fig. S9). Further discussion on the model-skill at seasonal, regional and inter-annual scales is provided in the Supplementary Information (Section 3 and 5).

Cluster analysis of $\acute{H}_s$ by member (Methods, Section 3.1) over the present-day time-slice delineates groups of ensemble members defined by wave-modelling methodology, rather than the GCM-forcing (Fig. 1). These results supported by Fig. S12 show that WMM strongly dominates the variance in this community ensemble of historical wave simulations (which includes all GCM-forced wave simulated data available to date). Within each WMM cluster, we note close association of members with similar GCM-forcing (that is, GCMs with shared dynamical cores).

Fig. 1 shows two well-defined statistically-derived clusters (1 and 5) explained by differences in the training datasets, transfer functions and/or predictor corrections, and three dynamically-based clusters (2-3 and 4) arising from differences in dynamical wave modelling configurations (e.g., model source-term parameterizations). Note that clusters 1 (IHC) and 5 (ECCC (s)) share a common characteristics, in which their members have very high similarity, as a consequence of their statistical calibrations and predictor corrections[33,47]. This is also evident in our model-skill comparison (Supplementary Figs. S1-S3, S12). Consult Supplementary Information (Section 4) for the details on the distinctive qualities of each cluster and for discussion on within-cluster similarities.

Projected future changes in the climatological mean wave fields over the globe by the end of the 21st century (2081-2100) are assessed for two representative concentration pathways: a medium (RCP4.5) and a high-emission scenario (RCP8.5). The RCP4.5 and RCP8.5 exhibit very similar spatial patterns of projected changes for all wave parameters but the RCP8.5 shows relatively larger changes (Fig. 2). Signals of projected changes in annual mean wave parameters ($\acute{H}_s$, $\acute{T}_m$, and $\acute{\theta}_m$) shows robust change (Methods, Section 5) over ~36%, 44% and 32% of global ocean, respectively (under RCP8.5) (Table S2).

A robust projected decrease in annual $\acute{H}_s$ is seen across the North Atlantic Ocean and portions of the northern Pacific Ocean of up to ~10% under RCP8.5, expanding further across the eastern Indian and southern Atlantic Oceans in Austral summer. This is consistent with the relatively uniform decrease in projected surface wind speeds over the boreal extra-tropical storm belt[48] partially driven by a strongly reduced meridional temperature gradient due to the polar amplification of climate change[49]. The areas of robust projected increase are limited to the Southern Ocean and the tropical eastern Pacific - in line with the intensification and poleward shift of the austral westerly storm belt[50] and increasing Southern Ocean swell propagation into the tropical areas[23] respectively. In the Austral winter, regions of robust projected increase expand further across the tropics. These findings are overall qualitatively consistent with the Coordinated Ocean Wave Climate Project (COWCLIP) CMIP3 multi-model ensemble[23], and other relevant literature[21].

Storm significant wave height H_s^{99} show similar annual/seasonal characteristics of change as for $\acute{H}_s$, however, the fraction of global ocean showing robust changes is much smaller (Fig. 2, Supplementary Table S2) highlighting the high uncertainty in extreme wave climate projections. Although we present changes in projected changes in extreme H_s^{99}, we draw attention to the ongoing challenge of resolving storm wave conditions generated by intense tropical/extra-tropical storms in wave simulations forced directly with atmospheric surface fields (~1-2°) from CMIP5 GCMs. High-resolution studies[33,34] have highlighted the importance of increased wind forcing resolution (~0.25°) to adequately capture storm wave climate in tropical cyclone-affected areas, and the sensitivity of projected changes to resolution.

The extended influence of the increasing propagation of swells from the Southern Ocean region into the tropics is shown by the robust projected increase in $\acute{T}_m$ (~44% of the global ocean region) and the projected shift in $\acute{\theta}_m$ over ~32% of the global ocean (clockwise over the tropical Pacific and tropical Atlantic, and anti-clockwise elsewhere). Consult the Supplementary Information (Figs. S21-S22) for further discussion on the projected future seasonal changes. The results described are mechanistically linked to well-documented large-scale atmospheric wind circulation changes[48,49] and modes of natural climate variability[23].

Beyond evaluating the robustness of the projected changes (Fig. 2), we assess the importance of the changes relative to the magnitude of the present-time inter-annual variability (see Supplementary Fig. S20). For RCP4.5, and we speculate the same for lower pathways[51], most robust projected changes in wave parameters fall within the range of present natural variability (<100%). Under the high-emission RCP8.5 however, nearly all robust changes exceed the simulated present-day inter-annual variability (some regions >150%).

Fig. 3 identifies robust projected changes in offshore multivariate wave conditions (H_s, T_m and θ_m) in the vicinity of the world's coastlines (Methods Section 6), which are considered dominant physical drivers of coastal change[5,6,13,52] and have served as a proxy for broad-scale assessments of coastal risk and vulnerability[26,35,36,53]. We find ~50% of the world's coasts (excluding sea-ice areas and enclosed-basins) exhibit robust projected changes in the adjacent offshore wave climate in at least one variable ($\acute{H}_s$, $\acute{T}_m$ or $\acute{\theta}_m$). Whilst there are regions where robust projections are limited to a single variable (e.g., $\acute{\theta}_m$ changes off the southern and eastern coasts of Africa), there are several coastal sections (~40% of the global coastline) where robust changes in offshore $\acute{H}_s$, $\acute{T}_m$ and/or $\acute{\theta}_m$ coincide (e.g., New Zealand, Southern Australia and the western coasts of Central and South America). This is also the case for the highly populated North American Atlantic coast (a well-documented hotspot of accelerated sea-level rise[54], where we find a robust decrease in $\acute{H}_s$ and $\acute{T}_m$. Future projected changes in $\acute{\theta}_m$ (a key driver of sustained coastal erosion[55]) are robust in the vicinity of 21% of the word's coastlines with magnitudes ranging between ~±17°. We exclude sea-ice affected regions from our analysis. However, these areas must be acknowledge as locations of potential high future wave climate change, owing to altered wind and fetch conditions with changing sea-ice extent[29,56].

Our community-ensemble of global wave-climate projections has a range of uncertainty stemming from several different sources (RCPs, GCMs and WMMs), which have remained largely unquantified in previous, standalone studies. We applied Ward's ANOVA-based clustering (Methods, Section 3.2) to a designed subset of projection scenarios (Table S3) spanning 2 RCP emissions scenarios, 10 GCM models and 8 WMMs, providing an overall analysis of similarity amongst the projected changes (Fig. 4). We find that projected relative changes in $\acute{H}_s$ largely cluster by GCM-forcing (i.e., the atmospheric forcing from which the wave field originates). There are only a few cases, where RCP/WMM-related uncertainties dominate the dissimilarity between projections (e.g. MIROC5, BCC-CSM1.1 or CNRM-CM5-forced members). See the Supplementary Information (Section 6.3) for further discussion on the distinctive qualities of each cluster (Section 6.3).

To further quantify the dominant drivers of uncertainty among these global wave climate projections and their relative contribution to the total projection uncertainty, we applied a three-factor ANOVA-based variance decomposition to three opportunity subsets (Table S4) containing all three sources of uncertainty. See the Methods (Section 4) for a description of the selection of the subsets used and the ANOVA methodology. The findings show that no single source of uncertainty is negligible, and that the full projection uncertainty is not solely attributable to the different sources of uncertainty, but also depends on their interactions. For all subsets available (Fig. 5, Supplementary Figs. S27-S28) we find a dominating influence of GCM uncertainty across most of the global ocean, accounting for ~30% to more than 50% of the total uncertainty associated with projected future changes in the climatological mean $\acute{H}_s$. These results are consistent with our cluster analysis (cf. Fig. 4).

Scenario-driven uncertainty dominates over the North Atlantic, western North Pacific and Southern Ocean (~40% to more than 50% of the full uncertainty) but is exceeded by other uncertainty contributors elsewhere. Choice of WMMs is a significant contributor to the full uncertainty, particularly across the tropics/subtropics (~25-50%), and the interactions between uncertainty sources account for ~20-~30% of the total uncertainty across most of the world's oceans (dominated by GCM-WMM interactions, Fig. 5e). These findings show that all the three sources of uncertainty must be adequately sampled to capture the full uncertainty in the projected change signal. It also demonstrates that previous studies relying on a single methodology have not captured up to ~40-50% of the total uncertainty space (that is, the sum of all the fractions related to WMM).

Our global-scale study does not resolve the uncertainty in projections of wave fields introduced with atmospheric downscaling techniques. Although the regional downscaling step has been widely used in wave climate projection studies, and is a topic of intensive research[57], the several different downscaling techniques introduce an additional source of uncertainty which (at present) is not possible to sample at the global-ocean scale.

Our CMIP5-based coordinated ensemble of wave-climate projections samples over RCP, GCM and WMMs, thus allowing a much improved sampling of the uncertainty space relative to the COWCLIP CMIP3-based ensemble of opportunity[23], or any previous study to date[21]. In addition to resolving the largely unquantified contribution of all three dominant sources of uncertainty, this study attests to the importance of considering conceptually distinct wind-wave methodologies. We note that, some of the uncertainty seen amongst dynamical simulations in terms of H_s biases could be potentially reduced by further model calibration[58,59] and improved wind-wave model physics (e.g., removing dependence on spectral model approximations, such as for nonlinear wave-wave interactions[60] and model limiters for spectral propagation velocities, applied to improve computational efficiency and accuracy[61,62]). While, at the moment, it is not possible to isolate these components, we advocate that future dynamical wave studies attempt to reduce the overall H_s historical bias. Regarding model skill, wind forcing correction could lead to improved wave model simulations[59]. The results also stress the need to better understand how different global wave reanalysis and hindcasts (used to develop historical trends of wave climate change[1,63]) differ.

Our results provide a new perspective on the robustness of multivariate global-scale wave projections which builds far beyond the restricted range of future wave-climate scenarios published in individual studies to date. These coordinated ensemble projections show signals of wave climate change will not exceed the magnitude of the natural climate variability if the goal of the Paris Agreement 2° C degree target is kept. Under a high-emission scenario (RCP8.5), ~48% of the world's coast is at risk of wave climate change, owing to changes in offshore forcing $\acute{H}_s$, $\acute{T}_m$ and/or $\acute{\theta}_m$ (with ~40% exhibiting robust changes in at least two of these wave variables). The magnitude of the future projected changes found for any of these wave variables (~5-15%) is capable of inducing significant changes in coastal wave-driven processes and their associated hazards[52].

Broad-scale assessments of coastal impacts of climate change are beginning to consider changes to wave climate[1,35,36,53] however, these studies are yet to consider directional shifts in wave propagation, which have been shown to be a dominant driver of shoreline stability[5,13]. Whilst our results have far-reaching implications from many perspectives, they only address meteorologically-driven changes in wind-wave characteristics, which have been the predominant focus of wind-wave climate projection studies to date. Some localised-scale studies suggest the morphologically-driven component of wave climate change might lead to a greater change in the coastal zone than these meteorologically-driven changes[11]. Concentrated community effort is now required to quantify morphologically-driven wave climate change as a contributor to global coastal water-level changes, as we look towards improved coastal vulnerability assessments from the climate community[64].

Main text references.

1 Melet, A., Meyssignac, B., Almar, R. & Le Cozannet, G. Under-estimated wave contribution to coastal sea-level rise. Nature Climate Change 8, 234-239, doi:10.1038/s41558-018-0088-y (2018).

2 Serafin A. K., Ruggiero, P. & Stockdon, H.F. The relative contribution of waves, tides, and nontidal residuals to extreme total water levels on U.S. West Coast sandy beaches. Geophysical Research Letters 44, 1839-1847, doi:10.1002/2016GL071020 (2017).

3 Harley, M. D. et al. Extreme coastal erosion enhanced by anomalous extratropical storm wave direction. Scientific Reports 7, 6033, doi:10.1038/s41598-017-05792-1 (2017).

4 Barnard, P. L. et al. Extreme oceanographic forcing and coastal response due to the 2015-2016 El Niño. Nature communications 8, 14365-14365, doi:10.1038/ncomms14365 (2017).

5 Barnard, P. L. et al. Coastal vulnerability across the Pacific dominated by El Niño/ Southern Oscillation. Nature Geoscience 8, 801, doi:10.1038/ngeo2539

6 Hoeke, R. K. et al. Widespread inundation of Pacific islands triggered by distant-source wind-waves. Global and Planetary Change 108, 128-138, https://doi.org/10.1016/j.gloplacha.2013.06.006 (2013).

7 Feagin, R. A. et al. Does vegetation prevent wave erosion of salt marsh edges? Proceedings of the National Academy of Sciences 106, 10109-10113, doi:10.1073/pnas.0901297106 (2009).

8 Young, I. R, Ribal, Agustinus. Multiplatform evaluation of global trends in wind speed and wave height. Science 364, 6440, 548-552, doi:10.1126/science.aav9527 (2019).

9 Wandres, M., Pattiaratchi, C. & Hemer, M. A. Projected changes of the southwest Australian wave climate under two atmospheric greenhouse gas concentration pathways. Ocean Modelling 117, 70-87, https://doi.org/10.1016/j.ocemod.2017.08.002 (2017).

10 Albert, S. et al. Interactions between sea-level rise and wave exposure on reef

island dynamics in the Solomon Islands. Environmental Research Letters 11, 054011, doi:10.1088/1748-9326/11/5/054011 (2016).

11 Oliveira, F. S. B. F. A Case Study of Wave Climate Changes due to Nearshore Morphological Evolution. Journal of Coastal Research 24, 21-32 (2008).

12 Storlazzi, C. D. et al. Most atolls will be uninhabitable by the mid-21st century because of sea-level rise exacerbating wave-driven flooding. Science Advances 4, doi:10.1126/sciadv.aap9741 (2018).

13 Ranasinghe, R. Assessing climate change impacts on open sandy coasts: A review. Earth-Science Reviews 160, 320-332, https://doi.org/10.1016/j.earscirev.2016.07.011 (2016).

14 Coelho, C., Silva, R., Veloso-Gomes, F. & Taveira-Pinto, F. Potential effects of climate change on northwest Portuguese coastal zones. ICES Journal of Marine Science 66, 1497-1507, doi:10.1093/icesjms/fsp132 (2009).

15 Suh, K.-D., Kim, S.-W., Mori, N. & Mase, H. Effect of Climate Change on Performance-Based Design of Caisson Breakwaters. Journal of Waterway, Port, Coastal, and Ocean Engineering 138, 215-225, doi:10.1061/(ASCE)WW.1943-5460.0000126 (2012).

16 Cowell, P. J., Roy, P. S. & Jones, R. A. Simulation of large-scale coastal change using a morphological behaviour model. Marine Geology 126, 45-61, doi:https://doi.org/10.1016/0025-3227(95)00065-7 (1995).

17 Hurst, M. D., Rood, D. H., Ellis, M. A., Anderson, R. S. & Dornbusch, U. Recent acceleration in coastal cliff retreat rates on the south coast of Great Britain. Proceedings of the National Academy of Sciences 113, 13336-13341, doi:10.1073/pnas.1613044113 (2016).

18 Tebaldi, C., Arblaster, J. M. & Knutti, R. Mapping model agreement on future climate projections. Geophysical Research Letters 38, doi:10.1029/2011GL049863 (2011).

19 Magnan, A. K. et al. Addressing the risk of maladaptation to climate change. Wiley Interdisciplinary Reviews: Climate Change 7, 646-665, doi:10.1002/wcc.409 (2016).

20 Jones, R. N. et al. in Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (eds C. B. Field et al.) Ch. 2, 195-228 (Cambridge University Press, 2014).

21 Morim, J., Hemer, M., Cartwright, N., Strauss, D. & Andutta, F. On the concordance of 21st century wind-wave climate projections. Global and Planetary Change 167, 160-171, https://doi.org/10.1016/j.gloplacha.2018.05.005 (2018).

22 Hemer, M. A., Wang, X. L., Weisse, R. & Swail, V. R. Advancing Wind-Waves Climate Science. Bulletin of the American Meteorological Society 93, 791-796, doi:10.1175/BAMS-D-11-00184.1 (2012).

23 Hemer, M. A., Fan, Y., Mori, N., Semedo, A. & Wang, X. L. Projected changes in wave climate from a multi-model ensemble. Nature Climate Change 3, 471, doi:10.1038/nclimate1791, https://www.nature.com/articles/nclimate1791.

24 Church, J. A. et al. Sea Level Change. In: Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley (eds.)]. (Cambridge, United Kingdom and New York, NY, USA., 2013).

25 Hemer, M. A. & Trenham, C. E. Evaluation of a CMIP5 derived dynamical global wind wave climate model ensemble. Ocean Modelling 103, 190-203, https://doi.org/10.1016/j.ocemod.2015.10.009 (2016).

26 Mentaschi, L., Vousdoukas, M. I., Voukouvalas, E., Dosio, A. & Feyen, L. Global changes of extreme coastal wave energy fluxes triggered by intensified teleconnection patterns. Geophysical Research Letters 44, 2416-2426, doi:10.1002/2016GL072488 (2017).

27 Erikson, L. H., Hegermiller, C. A., Barnard, P. L., Ruggiero, P. & van Ormondt, M. Projected wave conditions in the Eastern North Pacific under the influence of two CMIP5 climate scenarios. Ocean Modelling 96, 171-185, https://doi.org/10.1016/j.ocemod.2015.07.004 (2015).

28 Bricheno, L. M. & Wolf, J. Future wave conditions of Europe, in response to high-end climate change scenarios. Journal of Geophysical Research: Oceans 0, doi:10.1029/2018JC013866 (2018).

29 Casas-Prat, M., Wang, X. L. & Swart, N. CMIP5-based global wave climate projections including the entire Arctic Ocean. Ocean Modelling 123, 66-85, https://doi.org/10.1016/j.ocemod.2017.12.003 (2018).

30 Semedo, A. et al. CMIP5-Derived Single-Forcing, Single-Model, and Single-Scenario Wind-Wave Climate Ensemble: Configuration and Performance Evaluation. Journal of Marine Science and Engineering 6, 90 (2018).

31 Timmermans, B., Stone, D., Wehner, M. & Krishnan, H. Impact of tropical cyclones on modeled extreme wind-wave climate. Geophysical Research Letters 44, 1393-1401, doi:10.1002/2016GL071681 (2017).

32 Tomoya, S., Nobuhito, M. & A., H. M. Variability and future decreases in winter wave heights in the Western North Pacific. Geophysical Research Letters 43, 2716-2722, doi:10.1002/2016GL067924 (2016).

33 Camus. P. et al. Statistical wave climate projections for coastal impact assessments. Earth's Future 5, 918-933, doi:10.1002/2017EF000609 (2017).

34 Wang, X. L., Feng, Y. & Swail, V. R. Climate change signal and uncertainty in CMIP5-based projections of global ocean surface wave heights. Journal of Geophysical Research: Oceans 120, 3859-3871, doi:10.1002/2015JC010699 (2015).

35 Vousdoukas, M. I. et al. Global probabilistic projections of extreme sea levels

show intensification of coastal flood hazard. Nature Communications 9, 2360, doi:10.1038/s41467-018-04692-w (2018).

36 Vousdoukas, M. I. et al. Climatic and socioeconomic controls of future coastal flood risk in Europe. Nature Climate Change 8, 776-780, doi:10.1038/s41558-018-0260-4 (2018).

37 Hinkel, J. et al. Coastal flood damage and adaptation costs under 21st century sea-level rise. Proceedings of the National Academy of Sciences 111, 3292-3297, doi:10.1073/pnas.1222469111 (2014).

38 Hallegatte, S., Green, C., Nicholls, R. J. & Corfee-Morlot, J. Future flood losses in major coastal cities. Nature Climate Change 3, 802, doi:10.1038/nclimate1979 https://www.nature.com/articles/nclimate1979.

39 Wahl, T. et al. Understanding extreme sea levels for broad-scale coastal impact and adaptation analysis. Nature Communications 8, 16075, doi:10.1038/ncomms16075 https://www.nature.com/articles/ncomms16075.

40 Arkema, K. K. et al. Coastal habitats shield people and property from sea-level rise and storms. Nature Climate Change 3, 913, doi:10.1038/nclimate1944 https://www.nature.com/articles/nclimate1944.

41 Hemer, M., Wang, X., Webb, A. & contributors, C. Report of the 2018 Meeting for the WCRP-JCOMM Coordinated Ocean Wave Climate Project (COWCLIP). (Paris, France, 2018).

42 Hemer, M., Wang, W., Charles, E., Hegermiller, C., and COWCLIP contributors. Report of the 2014 Meeting for the WCRP-JCOMM Coordinated Global Wave Climate Projections (COWCLIP). (Paris, 2014).

43 Ribal, A. & Young, I. R. 33 years of globally calibrated wave height and wind speed data based on altimeter observations. Scientific Data 6(1):77, doi:10.1038/s41597-019-0083-9 (2019).

44 Stopa, J. E. & Cheung, K. F. Intercomparison of wind and wave data from the ECMWF Reanalysis Interim and the NCEP Climate Forecast System Reanalysis. Ocean Modelling 75, 65-83, doi:https://doi.org/10.1016/j.ocemod.2013.12.006 (2014).

45 Dee, D. P. et al. The ERA-Interim reanalysis: configuration and performance of the data assimilation system. Quarterly Journal of the Royal Meteorological Society 137, 553-597, doi:10.1002/qj.828 (2011).

46 Taylor, K. E. Summarizing multiple aspects of model performance in a single diagram. Journal of Geophysical Research: Atmospheres 106, 7183-7192, doi:10.1029/2000JD900719 (2001).

47 Wang, X. L., Feng, Y. & Swail, V. R. Changes in global ocean wave heights as projected using multimodel CMIP5 simulations. Geophysical Research Letters 41, 1026-1034, doi:10.1002/2013GL058650 (2014).

48 Kar-Man Chang, E. CMIP5 Projected Change in Northern Hemisphere Winter

Cyclones with Associated Extreme Winds. Journal of Climate 31, 6527-6542, doi:10.1175/JCLI-D-17-0899.1 (2018).
49 Karnauskas, K. B., Lundquist, J. K. & Zhang, L. Southward shift of the global wind energy resource under high carbon dioxide emissions. Nature Geoscience 11, 38-43, doi:10.1038/s41561-017-0029-9 (2018).
50 Sigmond, M., Reader, M. C., Fyfe, J. C. & Gillett, N. P. Drivers of past and future Southern Ocean change: Stratospheric ozone versus greenhouse gas impacts. Geophysical Research Letters 38, doi:10.1029/2011GL047120 (2011).
51 Millar, R. J. et al. Emission budgets and pathways consistent with limiting warming to 1.5 °C. Nature Geoscience 10, 741, doi:10.1038/ngeo3031, https://www.nature.com/articles/ngeo3031 (2017).
52 Sierra, J. P. & Casas-Prat, M. Analysis of potential impacts on coastal areas due to changes in wave conditions. Climatic Change 124, 861-876, doi:10.1007/s10584-014-1120-5 (2014).
53 Vousdoukas, M. I., Mentaschi, L., Voukouvalas, E., Verlaan, M. & Feyen, L. Extreme sea levels on the rise along Europe's coasts. Earth's Future 5, 304-323, doi:10.1002/2016EF000505 (2017).
54 Sallenger Jr, A. H., Doran, K. S. & Howd, P. A. Hotspot of accelerated sea-level rise on the Atlantic coast of North America. Nature Climate Change 2, 884, doi:10.1038/nclimate1597, https://www.nature.com/articles/nclimate1597.
55 Barnard, P. L. et al. Extreme oceanographic forcing and coastal response due to the 2015–2016 El Niño. Nature Communications 8, 14365, doi:10.1038/ncomms14365 https://www.nature.com/articles/ncomms14365.
56 Khon, V. C. et al. Wave heights in the 21st century Arctic Ocean simulated with a regional climate model. Geophysical Research Letters 41, 2956-2961, doi:10.1002/2014GL059847 (2014).
57 Jacob, D. et al. EURO-CORDEX: new high-resolution climate change projections for European impact research. Regional Environmental Change 14, 563-578, doi:10.1007/s10113-013-0499-2 (2014).
58 Stopa, J. E. Wind forcing calibration and wave hindcast comparison using multiple reanalysis and merged satellite wind datasets. Ocean Modelling 127, 55-69, doi:https://doi.org/10.1016/j.ocemod.2018.04.008 (2018).
59 Campos, R. M., Alves, J. H. G. M., Guedes Soares, C., Guimaraes, L. G. & Parente, C. E. Extreme wind-wave modeling and analysis in the south Atlantic Ocean. Ocean Modelling 124, 75-93, https://doi.org/10.1016/j.ocemod.2018.02.002 (2018).
60 Hasselmann, S., Hasselmann, K., Allender, J. H. & Barnett, T. P. Computations and Parameterizations of the Nonlinear Energy Transfer in a Gravity-Wave Specturm. Part II: Parameterizations of the Nonlinear Energy Transfer for Application in Wave Models. Journal of Physical Oceanography 15, 1378-1391

(1985).
61 van Vledder, G. P., C. Hulst, S. T. & McConochie, J. D. Source term balance in a severe storm in the Southern North Sea. Ocean Dynamics 66, 1681-1697, doi:10.1007/s10236-016-0998-z (2016).
62 Dietrich, J. C. et al. Limiters for spectral propagation velocities in SWAN. Ocean Modelling 70, 85-102, https://doi.org/10.1016/j.ocemod.2012.11.005 (2013).
63 Reguero, B. G., Losada, I. J. & Méndez, F. J. A recent increase in global wave power as a consequence of oceanic warming. Nature Communications 10, 205, doi:10.1038/s41467-018-08066-0 (2019).
64 Stammer, D., Roderik van der Wal, Robert J. Nicholls & Schlosser, P. WCRP/IOC Sea Level 2017 Conference Statement. International WCRP/IOC Conference 2017 - Regional Sea Level Changes and Coastal Impacts. (Columbia University, New York, US, 2017).

List of Figure captions

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

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

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

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

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

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

Fig. 5 - Relative contribution of different sources of uncertainty to the projected future changes in the mean of annual/seasonal significant wave height ($\acute{H}_s$). a-d, Fraction of the total uncertainty (variance) in the projected $\acute{H}_s$ changes (2081-2100 relative to 1979-2004) attributable to **a)** global climate models (GCMs), **b)** wind-wave modelling methods (WMMs), **c)** representative concentration pathways (RCPs) and **d)** sum of all interaction terms. **e)** Spatially-averaged contribution of each uncertainty source and their pairwise and triple interactions to the total ensemble uncertainty. Results are derived from the ensemble subset 2 which consist of 6 GCMs, 2 RCPs and 3 WMMs for a total of N = 36 simulations (Supplementary Table S4). Similar results are found for subset 1 and 3 and are presented in Supplementary Fig. S16-S17. The variance partitioning is based on a three-factor ANOVA model complemented with a subsampling scheme (Methods, Section 6). Note that plotting artifacts such as horizontal lines reflect the effects of the spatial-domain partitioning applied in the statistical methodologies.

Methods.

1. Data contribution

We use a community-derived ensemble compiled from ten CMIP5-based global wind-wave climate projection studies[25-34], completed under a pre-designed framework[41,42]. Annual and seasonal means of significant wave height (H_s), mean wave period (T_m), mean wave direction (θ_m) as well as 10th/99th percentiles of annual/seasonal H_s are obtained from the ten individual studies. Consult Supplementary Information for a detailed description of the datasets considered and framework.

Our analysis assesses projected relative changes between the representative present-day (1979-2004) and future (2081-2100) time-slices. These time periods align with the CMIP5 GCM archives of high-temporal resolution atmospheric fields used to develop wind-wave projections; and correspond to the common period across nine of the ten contributing datasets (see Supplementary Section 1.1 Table S1). Contributed datasets are considered under two different greenhouse-gas representative concentration pathways: RCP4.5 and RCP8.5 describing medium-stabilizing and high-radiative forcing scenarios - reaching +4.5 W/m^2 and +8.5 W/m^2 (relative to pre-industrial 1850-conditions) respectively. Sea-ice regions were excluded from analysis to support inter-comparison between the different contributions.

2. Skill of GCM-forced wave climate simulations

As previously mentioned, all contributing studies[25-34] have provided assessments of the skill of their GCM-forced global wind-wave simulations to represent the historical wave climate on an independent basis. Here we use two historical wave datasets (a recently compiled dataset of altimeter measurement records and a well-known global wave reanalysis) exclusively as a common point of reference for our model ensemble inter-comparison. The two datasets are briefly described below.

2.1 Historical satellite altimeter measurements

We compare the GCM-forced wave simulations with the most recent (and complete) database[43] of satellite H_s measurements. This database combines 13 radar altimeters which have been extensively calibrated against the National Oceanographic Data Center (NODC) buoy data, and cross-validated against an independent compiled buoy dataset supplied by the ECMWF[43,65]. The dataset contains H_s on a 2° grid resolution (at global scale) over a period of 33 years (1985-2018). After control analysis, we found partial years over 1985-1989 (when only GEOSAT data is available) and no data available for 1991 which limits the data to 1992-2018, providing a common time-slice duration for comparison of 26 years.

In the comparison of the GCM-forced global wave simulations with the altimeter measurements, the time-slice mismatch is ignored[66]. Since the GCM atmospheric forcing (and the spectral wave models) were not subject to any data assimilation, they are considered as representative of the historical wave climate regardless of the time period[66]. Note that GCM simulations (and their natural internal climate variability and its associated large-scale modes) are not in temporal phase with the satellite database. We assume that any differences between GCMs and altimeter measurements are attributable to model and observation biases and not from the non-stationarity of the wind-wave climate[23].

To allow for intercomparison, the wave parameters obtained from each of the contributions[25-34] were collocated onto the satellite-database global grid preserving the original data. Taylor diagrams[46] were used to compare the skill of the GCM-forced wave simulations to represent the present H_s climate at both global and regional-scale (Supplementary Figs. S1-S3 and Figs. S4-S5 respectively). We clarify that our Taylor diagrams present a spatial pattern correlation of a temporal average (and not a spatio-temporal correlation). In addition to Taylor diagrams, we present global pairwise comparisons maps of the mean and variability H_s biases for a subset from the full ensemble with common GCM-WMM (Supplementary Table S3), allowing us to identify the spatial variations of the biases (Supplementary Figs. S12-S13, S16-S17, respectively).

2.2 ERA-Interim wave reanalysis

In addition to the univariate satellite data[45] we compare model-skill over the present-day wave climate (1979-2004), by comparing the present-day GCM-forced global wave simulations with the wind-wave parameters obtained from the observationally constrained ECMWF ERA-Interim[45] (ERAI) global wave reanalysis. The ERAI is a consistent spatially and temporally complete dataset[45], which has been widely used[1,25,67] and extensively validated[44] being considered appropriate for multi-year analysis and modeling of long-term processes[44]. The ERAI database provides 6-hourly values of H_s, T_m and θ_m on a 1° global resolution, allowing us to compare all wave variables of interest at global-scale. The ERAI is therefore used as a well-known reference database, allowing us to compare all contributing simulations under the same reference.

We note that, despite its relatively good model-skill against buoy and altimetry measurements[44], the ERAI still exhibits some biases in the H_s upper percentiles (95th and above), where it underestimates altimetry measurements of H_s by ~10-15%[44].

The original 6-hourly multivariate ERAI dataset was used to calculate a standard set of statistics as performed for the contributing studies[25-34] (see Supplementary Information, Section 2). To allow for intercomparison, the surface wave parameters derived from each of the contributing studies[25-34] were bilinearly interpolated onto the ERAI grid. Taylor diagrams[46] were adopted as a representation of the skill of the GCM-forced wave simulations to reproduce the present multivariate wave climate (H_s, T_m and θ_m) at both global and regional-scale (Supplementary Figs. S6-S8 and Fig. S9, respectively). The global pairwise comparison maps of mean and variability bias using the ERAI dataset are presented in Supplementary (Figs. S14-S14 and Figs. S18-S19).

3. Cluster methodology

We applied an agglomerative-hierarchical clustering analysis, with the similarity criterion defined by Ward's ANOVA-based minimum variance algorithm[68]. The clustering method was used without imposing any restrictions on the number and size, or a priori assumptions, of clusters. Initial cluster distances were derived using a multi-dimensional approach, where the pair-wise Euclidean distance (D¿ amongst ensemble members are calculated at every grid location rather than spatially-averaged, hence clustering members with high similarity in terms of spatial pattern and magnitude:

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

where $x_{i,k}$ and $x_{j,k}$ are the magnitudes of the relative projected change in the annual mean significant wave height from the GCMs i and j respectively, at grid point k, with w equal to the number of ocean grid points. Note that for the clustering of present-day wave simulations we have used absolute values rather than relative changes. The usage of annual mean significant wave height ($\acute{H}_s$) as our clustering variable is based on the fact that $\acute{H}_s$ is the only parameter available from all the contributions and our main objective is to analyse the total community ensemble of wave simulations. Note that, statistical-method-derived members[33,34] from ECCC (s) and IHC did not provide wave period and/or directions (Supplementary Table S1). We also carried out a multivariate clustering based on annual $\acute{H}_s$, $\acute{T}_m$ and $\acute{\theta}_m$ (not shown) using our dynamical subset of simulations, which showed qualitatively similar results to the $\acute{H}_s$-based clustering, in both the present-day simulations and projected relative changes. Further description of the clustering method application to the present-day climate and the projected relative changes is provided below.

3.1 Application to present-day simulations

Annual $\acute{H}_s$ from each GCM-forced global wave simulation over the present-day time-slice (1979 to 2004) was used in the clustering method (Eq. 1). We included all existing ensemble models as well as the mean of each individual contributing study ensemble, a uniformly weighted ensemble mean (i.e., attributing equal weight to individual member) and an ensemble mean weighted by WMM. The latter consisted of reducing the full ensemble to *n*-members with each single member representing the mean from a specific WMM (when suitable). For example the 30-model IHC ensemble was reduced to one member, representing its ensemble mean. The relative differences (%) between the average of all the members within each main cluster and the satellite data was calculated separately for each parameter, simply to highlight the key qualities of each cluster (Fig. 1 and Supplementary Fig. S10). The relative difference was also calculated using ERAI (Supplementary Fig. S11). Note that the clustering analysis (Fig. 1) is fully independent from the comparison with the satellite or the ERAI datasets as described in Section 3.

We applied the clustering analysis to annual and seasonal $\acute{H}_s$ values combined, and the results were consistent with those obtained using annual mean values. We also applied the clustering procedure to the other wave parameters (individually), and obtained consistent findings. In all cases, the present-day simulations are strongly dependent on the WMM adopted by each study group to develop future wave fields as shown in Fig. 1.

3.2 Application to projected future changes

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

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

where $\Delta H_{j,k}$ is the projected change by GCM j at each grid node k.

To resolve the relative importance of the three different sources of uncertainty (i.e. RCP scenarios, GCMs, and WMMs), we use a subset from the full community ensemble where each member shares common GCM forcing with at least two other members obtained from different WMMs (consult the Supplementary Table S2). In the clustering of projected relative changes (Eq. 1), we also included the mean of each study contribution, the uniformly weighted ensemble mean (Section 3.1), the ensemble mean weighted by GCM (section 5) and the ensemble mean weighted by WMM (for each RCP). Five key clusters were identified based on the clustering results as an indication of ensemble members with considerable dissimilarity in the projected change values. The mean of all members within each main cluster (when available) was calculated for each wave parameter (Fig. 1 and Supplementary Fig. S25), providing a robust indication of spatial and magnitude dissimilarities over the global ocean.

For completeness, we also applied the cluster analysis to the entire community ensemble of global wind-wave projections, yielding consistent dissimilarities and respective associations between all the available wave simulations (albeit less clear owing to the large size of the ensemble) (Fig. S26).

4. ANOVA methodology

4.1 Approach and selection of subsets

Uncertainty in the projected future wave climate changes (2081-2100 relative to 1979-2004) within our community-based multi-member ensemble arises from three different sources: choice of emission scenarios (RCPs), global climate models (GCMs), and wind-wave modelling methods (WMMs). The latter refers to the different statistical and dynamical wave modelling approaches used to simulate the global wind-wave fields (representing different configurations of statistical methods - such as transfer functions, training data sets and/or predictor corrections, and/or dynamical wave models including the source-term packages, sea-ice forcing and numerical model resolution). In contrast with other climatic variables (e.g., temperature or precipitation), dynamically-derived ensembles of wave projections are typically only available for 20-year period, constrained by the availability of high-temporal resolution GCM-simulated atmospheric surface winds[21,42] (Supplementary Table S2). This constrains testing the projection uncertainty against the natural (temporal) variability.

Hence, we decompose the total ensemble uncertainty in the projected changes in the long-term (20-year) mean of annual/seasonal $\acute{H}_s$ into contributions from the different sources of uncertainty (RCPs, GCMs and WMMs) and the interactions between them. The fraction of the uncertainty attributable to each source (at each grid node) is determined using a three-factor ANOVA[69]-based variance partition method (Section 4.3). The method was applied separately to three opportunity subsets obtained from the full ensemble, with each subset containing all three sources of uncertainty (Supplementary Table S3). No other subsets with the same number of factors exist in this community ensemble. Note that the forcing GCMs within subsets 2 and 3 represent a broad cross-section of the CMIP5 ensemble[49], particularly that with availability of high-temporal resolution surface wind fields, in terms of model components[70] and various GCM characteristics such as spatial resolution[70].

4.2 Subsampling scheme

The ANOVA-based variance decomposition using different sample sizes of variance sources result in biased variance estimators[71] (cf. Fig. 4 and Supplementary Fig. S27-S28 with Supplementary Fig. S29). To reduce such biases in the estimates of variance for quantification of the uncertainty contribution, we complemented the ANOVA based variance decomposition with a subsampling methodology previously proposed[71]. In each subsampling iteration i, we select two out of *n*-climate models and two out of *m*-wave models, representing a total of $C_2^n C_2^m$ subsamples, with n and m denoting the number of GCMs and WMMs within each subset respectively. For each subsample iteration i, we end up with two global climate models, two emission scenarios and two wind-wave-modelling approaches, which we used for variance decomposition as described below.

4.3 Three-factor ANOVA model based variance decomposition

Letting Y^i_{jkl} be our response variable, representing the projected change in $\acute{H}_s$ from the j^{th} GCM, k^{th} RCP and l^{th} WMM, we define our three-factor ANOVA-based partition model[71] without replication following[71,72]:

$$Y^i_{jkl} = \mu^i + \alpha^i_j + \beta^i_k + \gamma^i_l + (\alpha\beta)^i_{jk} + (\alpha\gamma)^i_{jl} + (\beta\gamma)^i_{kl} + \delta^i_{jkl} \tag{3}$$

where μ^i is the grand-mean projected change of the subsample i. The terms α^i_j, β^i_k, and γ^i_l represent the variance arising solely from the factors GCMs, WMMs, and RCPs (respectively), with j, k and l denoting samples of the different factors

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

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

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

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

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

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

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

$$\eta^2_{RCP-GCM-WMM} = \frac{1}{I}\sum_{i=1}^{I}\frac{SS\delta_i}{SST_i} \tag{10}$$

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

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:

$$\acute{x}_k = \frac{\sum_{i=1}^{n} \left(\Delta_{i,k} \times W_{i,k} \right)}{\sum_{i=1}^{n} \left(W_{i,k} \right)} \qquad (11)$$

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].

We assessed the significance of change projected by each of the ensemble members individually, with a two-tailed Welch's *t*-test that allows for different variances between over the present and future time-slices. The test was conducted at 5% significance level. To define areas of robust projected changes we first identified areas (grid points) where 50% or more of the ensemble members projected a significant change. Within these areas, we further identified the areas where 90% or more of the ensemble members exhibiting a significant change agreed on the sign of the projected changes; these are the areas of robust changes projected by the ensemble, and are hatched in Fig. 2. Note that we employed a higher threshold (90%) than the default 80%[18,75] for members' agreement on the sign of the projected changes. The key conclusions are similar if other IPCC-referenced methods were used to measure robustness[74].

As a complement to the robustness criteria[18] we further confirmed that, within all regions with robust projected changes, the ensemble mean of projected changes is statistically significantly different from zero (i.e. stands out of the inter-member variability) according to the result of one-sample student *t*-test at 5% significance level.

6. Percentage of coastline with robust changes in offshore forcing wave conditions

In this analysis, we consider all the available offshore deepwater (>~200 m) grid points, distributed along the global coast every ~100 km. The coast is taken from the Global Self-consistent Hierarchical High-resolution Geography database[76]. We limit our analysis to offshore changes owing to the limited ability of the CMIP5 GCMs to adequately capture fetch-limited, near-coastal wind fields and land-sea interactions (e.g., orographic and katabatic effects) given their coarse spatial resolution. Nevertheless, we note that our GCM-forced wave simulations exhibit good agreement against near-coast buoys[30,53], even within semi-enclosed seas (e.g. Mediterranean)[53] and in extreme wave conditions[77]. The model skill reported for near-coast buoys is comparable to that against offshore buoys and to high-resolution coastal wave hindcasts[78]. Sections of coast without available wave model outputs were not considered which included sea-ice areas and enclosed seas.

Data Availability

The data that support the findings of this study are available from the corresponding author upon request, or via the COWCLIP data access portal: https://cowclip.org/data-access/.

Methods References

65 Young, I. R., Sanina, E. & Babanin, A. V. Calibration and Cross Validation of a

Global Wind and Wave Database of Altimeter, Radiometer, and Scatterometer Measurements. Journal of Atmospheric and Oceanic Technology 34, 1285-1306, doi:10.1175/JTECH-D-16-0145.1 (2017).

66 Semedo, A. et al. Projection of Global Wave Climate Change toward the End of the Twenty-First Century. Journal of Climate 26, 8269-8288, doi:10.1175/JCLI-D-12-00658.1 (2013).

67 Kumar, P., Min, S.-K., Weller, E., Lee, H. & Wang, X. L. Influence of Climate Variability on Extreme Ocean Surface Wave Heights Assessed from ERA-Interim and ERA-20C. Journal of Climate 29, 4031-4046, doi:10.1175/JCLI-D-15-0580.1 (2016).

68 Ward, J. H. Hierarchical Grouping to Optimize an Objective Function. Journal of the American Statistical Association 58, 236-244, doi:10.1080/01621459.1963.10500845 (1963).

69 Storch, H. v. & Zwiers, F. W. Statistical Analysis in Climate Research. (Cambridge University Press, 1999).

70 Flato, G. et al. in Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (eds T. F. Stocker et al.) 741-882 (Cambridge University Press, 2013).

71 Bosshard, T. et al. Quantifying uncertainty sources in an ensemble of hydrological climate-impact projections. Water Resources Research 49, 1523-1536, doi:10.1029/2011WR011533 (2013).

72 Garcia, R. A., Burgess, N. D., Cabeza, M., Rahbek, C. & Araújo, M. B. Exploring consensus in 21st century projections of climatically suitable areas for African vertebrates. Global Change Biology 18, 1253-1269, doi:10.1111/j.1365-2486.2011.02605.x (2012).

73 Zhao, Y. et al. Potential escalation of heat-related working costs with climate and socioeconomic changes in China. Proceedings of the National Academy of Sciences 113, 4640, doi:10.1073/pnas.1521828113 (2016).

74 Collins, M. et al. Long-term Climate Change: Projections, Commitments and Irreversibility. In: Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley (eds.)]. (Cambridge University, New York, NY, USA, 2013).

75 Skinner, C. B. & Diffenbaugh, N. S. Projected changes in African easterly wave intensity and track in response to greenhouse forcing. Proceedings of the National Academy of Sciences 111, 6882, doi:10.1073/pnas.1319597111 (2014).

76 Wessel, P. & Smith, W. H. F. A global, self-consistent, hierarchical, high-resolution shoreline database. Journal of Geophysical Research: Solid Earth 101, 8741-8743, doi:10.1029/96JB00104 (1996).

77 Shope, J. B., Storlazzi, C. D., Erikson, L. H. & Hegermiller, C. A. Changes to extreme wave climates of islands within the Western Tropical Pacific throughout the 21st century under RCP 4.5 and RCP 8.5, with implications for island vulnerability and sustainability. Global and Planetary Change 141, 25-38, doi:https://doi.org/10.1016/j.gloplacha.2016.03.009 (2016).

78 Perez, J., Menendez, M. & Losada, I. J. GOW2: A global wave hindcast for coastal applications. Coastal Engineering 124, 1-11, https://doi.org/10.1016/j.coastaleng.2017.03.005 (2017).

Correspondence and requests for materials should be addressed to JM.

Acknowledgements.

This study represents Task 3 of the second phase of the Coordinated Ocean Wave Climate Project (COWCLIP) (https://cowclip.org/), an international collaborative working group endorsed by the Joint Technical Commission for Oceanography and Marine Meteorology (JCOMM) - a partnership between the World Meteorological Organization (WMO) and the Intergovernmental Oceanographic Commission of UNESCO (IOC-UNESCO). We acknowledge the different climate modelling groups, the Program for Climate Model Diagnosis and Intercomparison (PCMDI) and the World Climate Research Program's (WCRP) Working Group on Coupled Modelling (WGCM). We acknowledge ECMWF for availability of ERA-Interim data, and Australia's Integrated Marine Observing System (IMOS) for altimeter wind/wave data, used for model validation. J.M., M.H. and C.T. acknowledge the support of Australian Government National Environmental Science Program (NESP) Earth Systems and Climate Change Hub. B.T and M.W acknowledge the support of the Regional and Global Climate Modeling Program of the U.S. Department of Energy, Office of Science, Office of Biological and Environmental Research, through contract DE-AC02-05CH11231, and the National Energy Research Supercomputing Center (NERSC) of the Lawrence Berkeley National Laboratory. I.Y. acknowledges ongoing support from the Australian Research Council through grant DP160100738 and to Integrated Marine Observing System (IMOS). N.M, T.S, A.B and B.K. acknowledge the support of the TOUGOU Program by MEXT, Japan, JSPS-Kakenhi Program. L.E. acknowledges the support of the US Geological Survey Coastal and Marine Hazards/Resources Program. Ø.B and O.J.A acknowledge the support of the Research Council of Norway through the ExWaMar project through grant 256466. We thank all contributors to the COWCLIP project including, Christian Appendini (National Autonomous University of Mexico, Mexico), Fabrice Ardhuin (Ifremer, France), Nikolaus Groll (Helmholtz-Zentrum Geesthacht Zentrum, Germany), Sarah Gallagher (Met

Éireann, Ireland), Sergey Gulev (Moscow State University, Russia) and Will Perrie (Bedford Institute of Oceanography, Canada).

Authors Contribution

All authors (except CT, NC, MW, BT and FA) had input into experimental design via workshop.

JM led analysis of ensemble, algorithm development for data analysis and writing of manuscript; MH co-led and conceived the experiment, supervised analysis, provided CSIRO ensemble data, and co-wrote manuscript; XL co-led and conceived the experiment, developed community codes, provided ECCC ensemble data, and contributed to analysis and written manuscript; NC supervised analysis and contributed to written manuscript; CT provided CSIRO ensemble data, coordinated data, and contributed to written manuscript; IY provided satellite data, contributed to analysis and written manuscript; AS provided IHE ensemble data, contributed to analysis and written manuscript. NM and TS provided KU ensemble data and contributed to written manuscript; LE provided USGS ensemble data and contributed to written manuscript; OA & OB contributed ERA-Interim statistics; MD, AB & JoS contributed IHE ensemble data; LM contributed JRC ensemble data and developed community codes; MC-P contributed ECCC ensemble data and contributed to written manuscript; PC & MM contributed IHC ensemble data and contributed to written manuscript; BT and MW contributed LBNL ensemble data and contributed to written manuscript; LB and JW contributed NOC ensemble data; AW and BK had input via workshop; JuS contributed to analysis and written manuscript; FA assisted with figure development.