

Future Projections of Marine Heatwaves in the Indian Ocean under Different Socioeconomic Pathways

Jayarathna W. N. D. Sandaruwan^{a,b,c}, Wen Zhou^{a,b*}, Mat Collins^c, Oluwafemi E. Adeyeri^{a,b,d}, Xuan Wang^a, Paxson K. Y. Cheung^a, W.A E Lakshani^{a,b}, Zekai Ni^{a,b}

^a Low-Carbon and Climate Impact Research Centre, School of Energy and Environment, City University of Hong Kong, Kowloon, Hong Kong

^b Key Laboratory of Polar Atmosphere-Ocean-Ice System for Weather and Climate, Ministry of Education and Department of Atmospheric and Oceanic Sciences and Institute of Atmospheric Sciences, Fudan University, Shanghai, China

^c Department of Mathematics and Statistics, University of Exeter, Exeter, Devon, United Kingdom

^d Australian Rivers Institute, Griffith University, Nathan, QLD 4111, Australia

*Corresponding author: Wen Zhou, wen_zhou@fudan.edu.cn

Supplementary material

CMIP6 Models used in the study

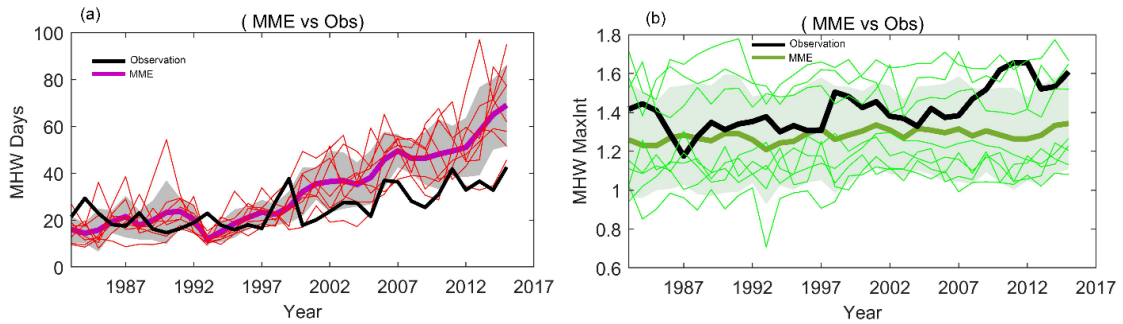
To analyse the historical and future simulated characteristics of MHWs, we use daily SST from 14 global climate model (GCM)s derived from Coupled Model Inter Comparison Project Phase 6 (CMIP6) database (more details are provided in the Table 1 in S1). Historical simulations from 1982 to 2014 and the future greenhouse gas emissions scenarios of Representative Concentration Pathways (RCP), which is integrated with shared socioeconomic pathways (SSPs) are selected from 2015 to 2100 (Eyring et al., 2016; Scafetta, 2023).

Table 1. Models that used for the study

	Institute	Institution ID	model	Ocean Model	resolution (km)	grid	country	reference
1	Commonwealth Scientific and Industrial Research Organization & Australian Research Council Centre of Excellence for Climate System Science, Australia (CSIRO-ARCCSS)	CSIRO-ARCCSS	CSIRO-ARCCSS.ACCESS-CM2	Modular Ocean Model v5 (MOM5)	100	360x300	Australia	
2	CSIRO-ARCCSS	CSIRO-ARCCSS	CSIRO.ACCESS-ESM1-5	MOM5	100	360x300	Australia	
3	Centre National de Recherches Meteorologiques (CNRM)	CNRM	CNRM-CERFACS.CNRM-CM6	NEMOv3.6	100	362x294	France	
4	Institut Pierre Simon Laplace (IPSL)	IPSL	IPSL.IPSL-CM6A-LR	NEMOv3.6	100	362x332	France	
5	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute, The University of Tokyo, National Institute for Environmental Studies (NIES), RIKEN Center for Computational Science	MIROC	MIROC.MIROC6	CCSR Ocean Component Model (COCO4.9)	100	360x256	Japan	
6	Max Planck Institute for Meteorology	MPI	MPI-M.MPI-ESM1-2-HR	Max Planck Institute for Meteorology Ocean Model (MPIOM1.6.3)	50	802x404	Germany	
7	Meteorological Research Institute	MRI	MRI.MRI-ESM2-0	MRI Community Ocean Model version 4 (MRI.COMv4)	100	360x363	Japan	
8		AWI	AWI.AWI-CM-1-1-MR	FESOM1.4	25	unstructured	Germany	

9	EC-Earth Consortium, Europe	EC-Earth-Consortium	EC-Earth-Consortium.EC-Earth3	NEMOv3.6	100	363x292	Europe	
10	EC-Earth Consortium, Europe	EC-Earth-Consortium	EC-Earth-Consortium.EC-Earth3-Veg	NEMOv3.6	100	362x292	Europe	
11	Nanjing University of Information Science and Technology, China	NUIST.NESM3	NESM3	NEMOv3.4	100	362x292	China	
12	National Center for Atmospheric Research, EUA	NCAR.CESM2	CESM2	Parallel Ocean Program version 2 (POP2)	100	360x180	Europe	
13	Center for International Climate and Environmental Research, Oslo, Norwegian Meteorological Institute, Oslo, Nansen Environmental and Remote Sensing Center, Bergen, Norwegian Institute for Air Research, Kjeller, University of Bergen, Bergen, University of Oslo, Oslo, Uni Research, Bergen	NCC.NorESM2-LM	NorESM2-LM	Miami Isopycnic Coordinate Ocean Model (MICOM)	100	360x384	Norway	
14	Canadian Centre for Climate Modeling and Analysis, Canada	CanESM5	CanESM5	Nucleus for European Modelling of the Ocean (NEMOv3.4.1)	100	361x290	Canada	

Fig. 1: Globally averaged observed and model MHW characteristics



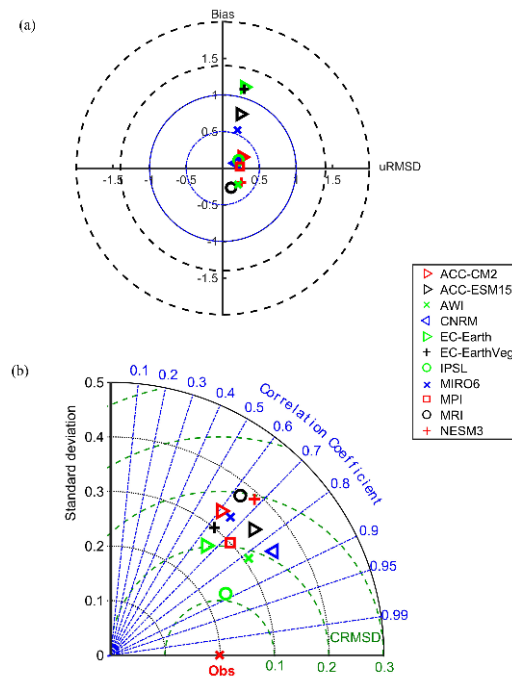
MHW days, (b) MHW maximum intensity for the period of 1982 to 2014. Black thick line shows the observed changes in MHW properties. The thick red line in (a) is the multi model ensemble mean (MME) for total MHW days, and (b) thick green line is the MME for maximum intensity. Smaller red lines (a), and green lines (b) indicate the output from individual MHW characteristics.

In this model performance evaluation process, we constructed the target diagrams and Taylor diagrams (Fig 2), to study about the statistical differences between model and the reference data (observation). These two diagrams are useful; hence they provide graphic summary how close the models to the observations. At the same time these two analyses provide several statistical metrics, that indicate the quantitative agreement with models and observations. Here we used main statistical metrics are correlation coefficient (R), the root-mean-square difference (RMSD), standard deviation (STD). The target diagram is derived by analyzing the bias, unbiased root mean square difference, and root mean square difference (RMSD), and the outputs displayed in the cartesian coordinates system where the x-axis indicate the RMSD' (variation of the error) and the y axis represent the bias (B). These three metrics can be combined using a one equation as follows:

$$RMSD^2 = B^2 + RMSD'^2 +$$

The RMSD is the distance from any point to the origin.

Fig. 2: Model evaluation based on target diagram and Taylor diagram



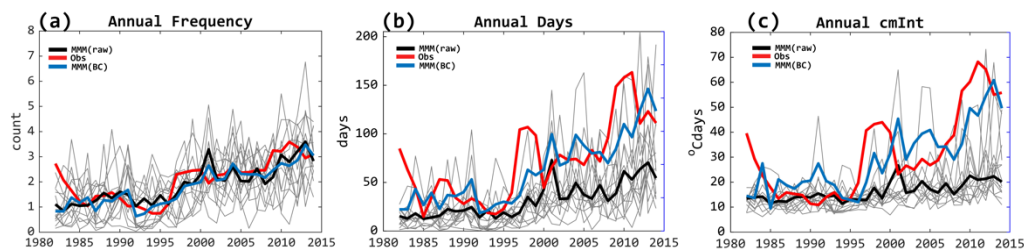
(a) Target diagram and the (b) Taylor diagram for all selected models for the sea surface temperature predictability in the global oceans. Each model, represent by different symbols.

Bias adjustment in model data

In this study we tried to reduce the inconsistencies between the simulated model outputs and observed outputs through bias correction (BC) method. In our work, we utilized a widely used univariate bias adjustment method known as quantile delta mapping (QDM) (Adeyeri et al., 2023; Cannon et al., 2015; Jose & Dwarakish, 2022; Maurer & Pierce, 2014). This method is employed to address biases in GCMs across various aspects such as the trend (Adeyeri et al., 2023). By applying QDM, we aimed to preserve the future climate change signal in the simulated outputs as it's a parametric quantile mapping method that can be used to preserve the trend in all quantiles (Cannon et al., 2015). We used this method as its minimize the bias in the mean of the climate models compared to the observational in spatial and temporal scales (Costa & Rodrigues, 2021; Maurer & Pierce, 2014). The main point here is that it use a transformation function to the future climate model outputs such as $X_{hist, fut}$ for variables like temperature it absolute changes will be preserved based on the following equation. This method

is applied to each model's outputs, where we utilize a calibration period from 1985 to 1999, and a validation period from 2001 to 2014.

Fig. 3: Multi model mean bias and bias adjusted CMIP6 models



Spatial average annual time series of (a) MHW frequency, (b) MHW total days, (c) MHW cumulative intensity where MMM of CMIP6 data before (black line) and after the QDM bias adjust (blue line), and plot together with observational output (red line). The small grey lines indicate the all 14 CMIP6 models, and their capability of detecting MHW properties particularly.

Reference:

- Adeyeri, O. E., Zhou, W., Laux, P., Ndehedehe, C. E., Wang, X., Usman, M., et al. (2023). Multivariate Drought Monitoring, Propagation, and Projection Using Bias-Corrected General Circulation Models. *Earth's Future*, 11(4), e2022EF003303. <https://doi.org/10.1029/2022EF003303>
- Cannon, A. J., Sobie, S. R., & Murdock, T. Q. (2015). Bias correction of GCM precipitation by quantile mapping: How well do methods preserve changes in quantiles and extremes? *Journal of Climate*, 28(17), 6938–6959. <https://doi.org/10.1175/JCLI-D-14-00754.1>
- Costa, N. V., & Rodrigues, R. R. (2021). Future Summer Marine Heatwaves in the Western South Atlantic. *Geophysical Research Letters*, 48(22). <https://doi.org/10.1029/2021GL094509>
- Eyring, V., Bony, S., Meehl, G. A., Senior, C. A., Stevens, B., Stouffer, R. J., & Taylor, K. E. (2016). Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization. *Geoscientific Model Development*, 9(5), 1937–1958. <https://doi.org/10.5194/gmd-9-1937-2016>
- Jose, D. M., & Dwarakish, G. S. (2022). Bias Correction and Trend Analysis of Temperature Data by a High-Resolution CMIP6 Model over a Tropical River Basin. *Asia-Pacific Journal of Atmospheric Sciences*, 58(1), 97–115. <https://doi.org/10.1007/S13143-021-00240-7/FIGURES/13>
- Maurer, E. P., & Pierce, D. W. (2014). Bias correction can modify climate model simulated precipitation changes without adverse effect on the ensemble mean. *Hydrology and Earth System Sciences*, 18(3), 915–925. <https://doi.org/10.5194/HESS-18-915-2014>

- Scafetta, N. (2023). CMIP6 GCM ensemble members versus global surface temperatures. *Climate Dynamics*, 60(9–10), 3091–3120. <https://doi.org/10.1007/s00382-022-06493-w>

