Progress in Oceanography 235 (2025) 103497

Contents lists available at ScienceDirect

Progress in Oceanography

journal homepage: www.elsevier.com/locate/pocean

Future climate projections in the global coastal ocean

Jason Holt[a,*], Anna Katavouta[a], Joanne Hopkins[a], Laurent O. Amoudry[a], Christian M. Appendini[b], Lars Arneborg[c], Alex Arnold[d], Yuri Artioli[e], Jerome Aucan[f], Barbara Berx[g], Laura Cagigal[h], Michela De Dominicis[a], Cléa Denamiel[i,j], Giovanni Galli[k], Jennifer A. Graham[l], Zoe Jacobs[m], Svetlana Jevrejeva[a], Bahareh Kamranzad[n], Clothilde Langlais[o], Morten Andreas Dahl Larsen[p], Andrea Lira-Loarca[q], Charlotte Lyddon[r], Moritz Mathis[s], Angélique Melet[t], Fernando Méndez[h], Sanne Muis[u,v], Paul Myers[w], Mairéad O'Donovan[x], Agnieszka Indiana Olbert[y], Matthew D. Palmer[d,z], Lachlan Phillips[o], Jeff Polton[a], Mercedes Pozo Buil[aa], Peter Robins[ab], Andrea Ruju[ac], Jodie A. Schlaefer[ad], Alfonso Senatore[ae], Samantha Siedlecki[af], Jonathan Tinker[d], Giorgia Verri[x], Ivica Vilibić[i,j], Xiaoyan Wei[a], Nadia Pinardi[ag]

[a] National Oceanography Centre, 6 Brownlow Street, Liverpool L3 6DA, UK
[b] Universidad Nacional Autónoma de México, 97356 Sisal, Mexico
[c] Swedish Meteorological and Hydrological Institute, Göteborgseskaderns Plats 3, SE-426 71 Västra Frölunda, Sweden
[d] Met Office, Fitzroy Road, Exeter EX1 3PB, UK
[e] Plymouth Marine Laboratory, Prospect Place, Plymouth PL1 3DH, UK
[f] The Pacific Community, B.P. D5, 98848 Noumea, New Caledonia
[g] Marine Directorate, Scottish Government, 375 Victoria Road, Aberdeen AB11 9DB, UK
[h] Universidad de Cantabria, Av. de los Castros, s/n, 39005 Santander, Cantabria, Spain
[i] Ruđer Bošković Institute, Bijenička Cesta 54, 10000 Zagreb, Croatia
[j] Institute for Adriatic Crops and Karst Reclamation, Put Duilova 11, 21000 Split, Croatia
[k] National Institute of Oceanography and Applied Geophysics (OGS), Borgo Grotta Gigante, 42/c, 34010 Sgonico TS, Italy
[l] Centre for Environment, Fisheries and Aquaculture Science (Cefas), Pakefield Road, Lowestoft NR330HT, UK
[m] National Oceanography Centre, European Way, Southampton SO14 3ZH, UK
[n] Department of Civil and Environmental Engineering, University of Strathclyde, Glasgow G11XJ, UK
[o] Commonwealth Scientific and Industrial Research Organisation (CSIRO), Castray Esplanade Battery Point, Tasmania 7004, Australia
[p] The Danish Meteorological Institute, Sankt Kjelds Pl. 11, 2100 Copenhagen, Denmark
[q] Department of Civil, Chemical and Environmental Engineering. University of Genoa, Via Montallegro 1, 16145 Genoa, Italy
[r] University of Liverpool, Chatham St, Liverpool L69 7ZT, UK
[s] Helmholtz-Zentrum Hereon, Max-Planck-Straße 1, 21502 Geesthacht, Germany
[t] Mercator Ocean International, 2 Av. de l'Aérodrome de Montaudran, 31400 Toulouse, France
[u] Vrije Universiteit Amsterdam, De Boelelaan 1105, 1081 HV Amsterdam, Netherlands
[v] Deltares, Boussinesqweg 1, 2629 HV Delft, Netherlands
[w] Department of Earth and Atmospheric Sciences, University of Alberta, Edmonton T6G 2E3, Canada
[x] CMCC Foundation – Euro-Mediterranean Center on Climate Change, Italy
[y] University of Galway, University Rd, Galway, Ireland
[z] School of Earth Sciences, University of Bristol, Queens Rd, Bristol BS8 1RJ, UK
[aa] University of California Santa Cruz, 99 Pacific St., Unit 255A, Monterey, CA 93940, USA
[ab] School of Ocean Sciences, Bangor University, Askew St, Menai Bridge LL595AB, UK
[ac] Department of Civil and Environmental Engineering and Architecture, University of Cagliari Via Marengo 2, 09123 Cagliari, Italy
[ad] Commonwealth Scientific and Industrial Research Organisation (CSIRO), James Cook University, James Cook Drive, Townsville, QLD 4811, Australia
[ae] University of Calabria, Via P. Bucci, 42/B, 87036 Rende, CS, Italy
[af] University of Connecticut, Department of Marine Sciences, 1080 Shennecossett Rd, Groton, CT 06340, USA
[ag] Decade Collaborative Center for Coastal Resilience, Department of Physics and Astronomy, University of Bologna, Via Berti Pichat 8, 40127 Bologna, BO, Italy

* Corresponding author.
E-mail address: jholt@noc.ac.uk (J. Holt).

https://doi.org/10.1016/j.pocean.2025.103497
Received 3 January 2025; Received in revised form 30 April 2025; Accepted 4 May 2025
Available online 8 May 2025

ARTICLE INFO

Keywords:
Coastal seas
Climate downscaling
Climate impacts
Coastal ocean modelling
Marine ecosystems
Coastal hazards
Marine economy

ABSTRACT

Resilient coastal communities and sustainable marine economies require actionable knowledge to plan for and adapt to emerging and potential future climate change, particularly in relation to ecosystem services and coastal hazards. Such knowledge necessarily draws heavily on coastal ocean modelling of future climate impacts, using a great diversity of both global and regional approaches to explore multiple societal challenges in coastal and shelf seas around the world. In this paper, we explore the challenges, solutions and benefits of developing a better coordinated and global approach to future climate impacts modelling of the coastal ocean, in the context of the UN Decade of Ocean Science for Sustainable Development project Future Coastal Ocean Climates (FLAME; part of the CoastPredict programme). Particularly, we address the need for diverse modelling approaches to meet different societal challenges, how regions can be harmonised through clustering and typology approaches, and how coordination of experimental designs can promote a better understanding of uncertainties and regional responses. Improved harmonisation of future climate impact projections in the global coastal ocean would allow sectoral and cross-sectoral global scale risk assessments, improve process understanding and help build capacity in under-represented areas such as the global south and small island developing states. We conclude with a proposed framework for a Global Coastal Ocean Model Intercomparison Project.

1. Introduction

1.1. Motivation

The impact of climate change on the marine environment is one of the greatest societal challenges of our time, described in detail by Cooley et al. (2023). Climatic effects on coastal hazards (such as flooding and erosion) brought about by sea level rise, storm surges and extreme waves put lives, livelihoods and infrastructure in coastal regions in danger. Climate change threatens the preservation of resilient and ecologically diverse marine ecosystems, and the sustainable harvesting of living marine resources. Accurate future projections are needed to better understand the impact of climate change on the coastal ocean and to strengthen the capacity of coastal communities to live with such impacts, by minimising the threats presented by climate change and maximising the opportunities.

The coastal ocean spans the marine environment from the continental shelf-slope to the landward limit of saline water and is a region of immense societal importance. The world's largest urban settlements boarder the coastal ocean, particularly beside estuaries. Currently, one billion people occupy land less than 10 m above current high tide limits, including 230 M below 1 m (Kulp and Strauss, 2019). For a moderate future greenhouse gas emissions scenario (RCP4.5) a total of 360 (310–420) million people will be threatened by annual flood events by 2100 (Kulp and Strauss, 2019). Coastal zones are threatened by sea level rise and an increasing frequency of extreme water levels, during which most damage occurs (e.g. Fox-Kemper et al., 2023; Vousdoukas et al., 2018). Global climate models consistently project a long term mean global sea level rise (Hamlington et al., 2020), which increases the frequency of storm surges and extreme waves (Fox-Kemper et al., 2023; Jevrejeva et al., 2023), and so low-lying populated coastlines are expected to be increasingly exposed to coastal hazards. Sea level rise induced risks include permanent submersion of coastal zones, coastal flooding, coastal erosion, salt intrusion in surface and ground water (with adverse impacts on drinking water and agriculture), drainage difficulties, and coastal ecosystems degradation or loss, e.g., of coastal wetlands and mangroves. Projected changes in the tracks, intensity and frequency of extreme storms are much less certain and highly regionally specific, but potentially compound these risks (Seneviratne et al., 2023). Similarly changes to riverine inputs to coastal seas, for example following extreme rainfall events, potentially enhances coastal pollution.

Coastal oceans provide a diverse range of ecosystem services, e.g. food production, coastal protection, carbon sequestration and cultural amenity, among many others. These are all, to varying degrees, vulnerable to climate change. Fisheries and aquaculture play an increasingly important role in providing food to growing populations. With changes in diets, aquatic food consumption is expected to increase by 15 % by 2030, with continued expansion expected primarily in aquaculture production (FAO, 2022). There are many projected impacts of climate change on marine life at a species, ecosystem and habitat level (Cooley et al., 2023), which are potentially confounded by trends in overfishing and land-sourced pollution. Increasing water temperature, reduced surface nutrients, ocean acidification and hypoxia are considered the most critical climate-induced ecosystem stressors in the open-ocean (Bopp et al., 2013), affecting species distributions and community structures throughout the food-web.

All sectors of the marine economy are potentially impacted by climate change, including shipping and maritime operations (e.g. due to changes in storm conditions and sea ice cover; Aksenov et al., 2017), tourism (e.g. due to harmful and nuisance algae), marine renewable energy (e.g. due to changes to wind and wave conditions), and energy and information cables (e.g. due to shifts in seabed morphology and wave climate; Bricheno et al., 2024).

Actions that will increase the resilience of the coastal ocean and its communities to future climate change require knowledge of:

1. The environmental **hazards**, their frequency, drivers and severity
2. The **exposure** of people, ecosystems, infrastructure and other assets to these hazards
3. The **vulnerability** of these exposed elements
4. Their ability to **adapt** to climate impacts

(IPCC, 2014)

While global climate models (GCMs) and earth system models (ESMs[1]) are our primary tools for understanding future changes in the climate system, they are not primarily designed as climate impact models. The models of the sixth (and most recent) phase of the Coupled Model Intercomparison Project (CMIP6) represent a significant improvement over previous phases of CMIP, for example, including more complex representation of biogeochemical interactions, improved cycling of alkalinity (Planchat et al., 2023), better cloud and precipitation schemes, and often higher spatial resolution. However, they are not designed as coastal ocean climate impact models and so are not well suited to this task, nor are they expected to be. Specifically, ESMs have comparatively low spatial resolution, exclude coastal ocean processes (see below and Holt et al., 2017; Ward et al., 2020) and have poor representation of complex bathymetry and coastlines. In CMIP6, complex ESMs typically have 100 km ocean resolution (but range from 50-100 km), whereas some ESMs have ocean resolutions as fine as 10–40 km (Hewitt et al., 2020). The higher resolution ESMs largely participate

[1] For simplicity the term ESM is used throughout this paper to refer to both coupled models of the physical climate (GCMs), and those with more complex biological and chemical components.

in HighResMIP (Haarsma et al., 2016), with a more limited protocol with fewer/different scenarios and reduced forecast horizon, e.g. only to 2050. The average resolution for ocean component models in CMIP6 was 58 km, compared with 87 km in CMIP5. While this is an improvement, it remains a long way from the minimum acceptable resolution in the coastal ocean (Holt et al., 2017). Moreover, ESMs generally neglect key coastal ocean processes such as tides, surface waves, benthic processes, and riverine inputs of carbon and nutrients. A similar situation is found in the resolution of the atmospheric component of these ESMs (50–250 km) with HighResMIP reaching 20–50 km. In the coastal ocean context, sufficient atmospheric resolution is crucial for providing geographic detail, coastal orographic effects and accurate extreme conditions (Iles et al., 2020).

Approaches using limited area and/or targeted sectoral (e.g. ocean-sea ice only) modelling (known as dynamical downscaling) provide the most commonly employed solution to address issues of resolution in both the ocean and atmosphere. For regional climate projections, this is organised through the Coordinated Regional Climate Downscaling Experiment (CORDEX; Giorgi, 2019; https://cordex.org/). While CORDEX does include ocean–atmosphere coupled protocols (e.g. Med-CORDEX; Somot et al., 2024) it is not focused on the coastal ocean, nor on coastal hazards or marine ecosystems, and many CORDEX regions only downscale the atmosphere. The Coordinated Ocean Wave Climate Project (COWCLIP; Hemer et al., 2012) provides a coordinated assessment of global wave climate models, aiming to provide guidelines for the analysis of wave models and standardize the analysis, particularly as related to future climate projections at global and regional scales (Morim et al., 2019). The Surge Model Intercomparison Project (SurgeMIP) aims to improve storm surge projections (Bernier et al., 2024), bringing together different global storm surge modelling systems to produce future projections and help coastal communities prepare for the impacts of climate change. Exploring the impacts of climate change on marine higher trophic levels and fisheries is the subject of FishMIP (Tittensor et al., 2018). FishMIP is one of many impacts modelling projects contributing to the Inter-sectoral Model Intercomparison Project (https://www.isimip.org/). There is not presently an analogous effort to coordinate studies focusing on the impacts of climate change in coastal and shelf seas.

The UN Decade of Ocean Science for Sustainable Development (UND) is focused on promoting sustainable development and addressing global challenges related to the ocean. It aims to strengthen scientific knowledge and partnerships and enhance the capacity of countries and communities to address ocean related issues. Endorsed by the UND, the Future Coastal Ocean Climates (FLAME) project aims to bridge the identified gap between the available state-of-the-art regional and global climate models and the need to provide more accurate climate projections of the entire earth system in coastal ocean environments. Working alongside the UND Collaborative Centre for Coastal Resilience and the CoastPredict Programme, and by developing a better understanding of the interactions between coastal ocean ecosystems, climate change, and human activities, FLAME aims to help ensure that all communities have the knowledge and resources necessary to increase their resilience to climate change in the coastal ocean. Capacity building in underrepresented areas, such as the global south and small island developing states, is a particular priority (Evans et al., 2024). The project will allow for sectoral and cross-sectoral global scale risk assessments by promoting collaboration and coordination across regions and modelling approaches.

Complimentary to FLAME, a joint Task Force on Regional Ocean Modelling and Climate Projections was convened in 2024 under the World Climate Research Programme (WCRP) CLIVAR-Ocean Model Development Pannel and CORDEX (https://cordex.org/strategic-activities/taskforces/task-force-on-regional-ocean-climate-projections/; CLIVAR-CORDEX-Ocean-TF). This Tasks Force aims to develop a strategic plan over 2025, notably to coordinate regional ocean climate projections (physics, biogeochemistry, sea-ice) worldwide by developing coordinated simulation protocols and by delivering standardized datasets, one of the goals being to improve regional ocean contribution to expert assessment reports (notably IPCC-AR7). The aspiration being that this plan evolves into a long-term CLIVAR-CORDEX initiative.

1.2. Overview of the paper

There is a diverse value chain involved in implementing a future climate downscaling study, particularly involving the interaction between multiple communities of practice (Fig. 1). No single modelling approach can represent the myriads of interacting earth system components in coastal ocean environments across all necessary spatiotemporal scales to adequately project coastal hazards and ecosystem response to climate change. Hence, we are faced with complex modelling choices and trade-offs, which we aim to explore here. In this paper we consider these choices from the perspective of how to deliver a more coordinated approach, particularly regarding the wide diversity of motivations for this activity and of resources to deliver it. Drenkard et al. (2021) propose a downscaling protocol for Living Marine Resource studies and this is readily generalised to wider applications. This paper addresses each of these aspects as follows:

- Problem analysis (Section 1 and 2):
  - o Essential processes
  - o Spatiotemporal scales
  - o Region selection
- Model selection (Section 3):
  - o Global and regional model choices
  - o Coupling and Earth System components
  - o Alternative approaches, including Machine Learning
- Uncertainty and simulation strategy (Section 4):
  - o Large scale regional climate change analysis
  - o Scenario selection
  - o Forcing selection:
    - ▪ Ocean (if not global),
    - ▪ Atmosphere (if not coupled),
    - ▪ Land (if not coupled)
    - ▪ All consistent and for particular future scenario(s)
  - o Forcing protocol (e.g. bias correction), initialisation and spin-up
  - o Transient versus time-slice versus climate-delta approach
  - o Validation and confidence
- Actionable knowledge (Section 5)
  - o Sharing code and data for end users and capacity development
  - o Co-design of expected outcomes with end users

The paper ends with a proposed outline framework for a future Global Coastal Ocean Model Intercomparison Project (GCO-MIP; Section 6). This would be organised in four inter-related Strands:

1. Common *meta*-data, assessment, diagnostics and best practice
2. Standard model experiments
3. Standard model regions and case studies
4. Data dissemination and end user communication

How the aspects of downscaling experiment design inform these strands is highlighted throughout the paper.

1.3. Background

The impacts of climate change in the coastal ocean arise from combinations of large-scale drivers via atmospheric, oceanic and terrestrial vectors. These drivers span the processes described in various chapters of IPCC WG I, and so will not be described in detail here. But to summarise, they include changes in:

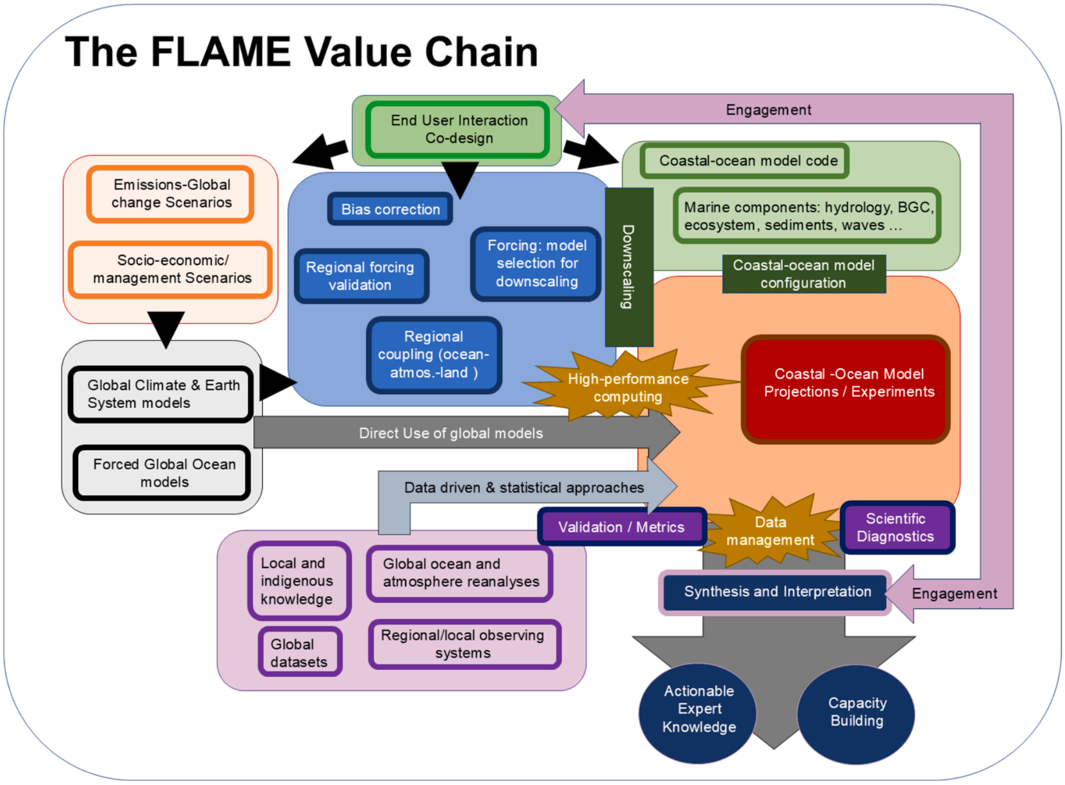

Fig. 1. The steps involved in developing actionable knowledge of climate impacts in the global coastal ocean. The different coloured regions loosely represent different communities of practice.

- Surface heat, water and momentum fluxes
- Large scale oceanic water masses and sea ice characteristics and distribution
- Large scale atmospheric and oceanic circulation
- Frequency, position and intensity of storms
- Extremes in air temperature and precipitation
- Atmospheric seasonality (e.g. monsoon cycles)
- Atmospheric chemical composition (e.g. increase in CO_2)
- Large-scale modes of climate variability (NAO, PDO, ENSO etc)
- Hydrological flows and riverine biogeochemical input

These large-scale drivers are modulated by regional and local processes, and the complexity of this interaction often implies that the coastal ocean climate change impacts differ qualitatively and quantitatively from their open-ocean counterparts, and the local response cannot be robustly determined from the large-scale drivers alone: some form of regionalisation is required. Here we briefly summarise, in general terms, the relevant coastal ocean processes (Fig. 2) that such downscaling studies might aim to understand and so add value to the wider scale view. Understanding these driver-response relationships sets the scales that need to be resolved, and processes included in any model experiment design.

Processes related to coastal ocean response to climate change

Surface warming is a ubiquitous effect of climate change. It

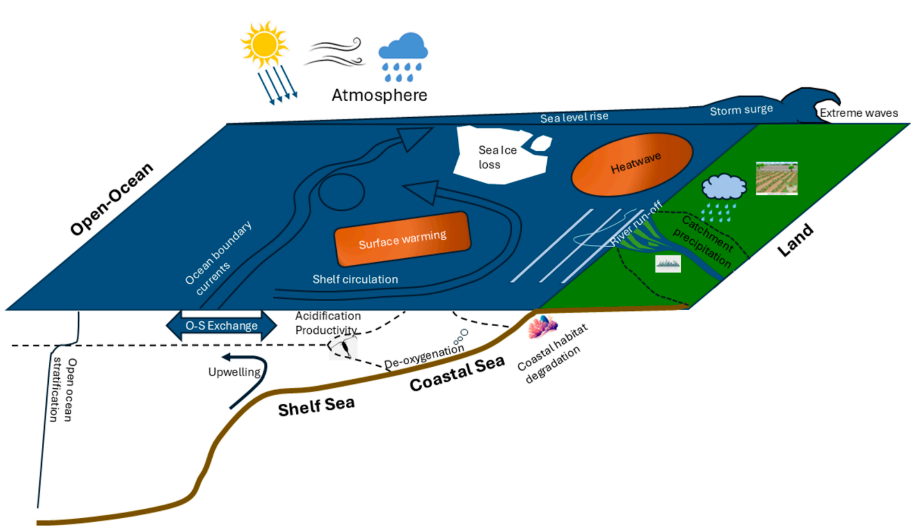

Fig. 2. Processes related to coastal ocean response to climate change.

increases coastal ocean permanent and seasonal stratification (Holt et al., 2022), which in turn reduces vertical turbulent fluxes, shoals mixed layers, decouples currents from topography, enhances fine scale processes (e.g. jets, eddies and internal waves) and modifies the density driven circulation patterns. The reduced vertical turbulent fluxes particularly decrease the re-supply of nutrients to depleted surface waters and inhibit the re-oxygenation of deeper waters. Increased temperature reduces the solubility of dissolved gases (e.g., O_2 and CO_2) and increases biogeochemical rates (e.g. remineralisation). Wider ecosystem effects include shifts, generally poleward, in species range boundaries. Warmer sea surface temperature (SST) also leads to rapid intensification and poleward movement of tropical cyclones, and thus storm surges and intense waves.

Marine heatwaves are prolonged periods of anomalously warm water that can extend over thousands of kilometres and can persist for several days or months (Hobday et al., 2016). They can be driven by changes in the advection and mixing of heat in the ocean or by atmospheric forcing (Berthou et al., 2024). These events have caused widespread impacts and disruption to marine ecosystems at surface and depth (e.g. Smale et al., 2019); coral bleaching being a notable example. Depending on their definition, they have generally increased in frequency, duration and intensity globally and are projected to increase further under climate change (Frölicher et al., 2018). A key open question is whether or not to change the baseline for marine heatwave identification with secular warming trends.

Increased open-ocean stratification is a robust response of the ocean to increased atmospheric temperatures and surface freshwater input (Fox-Kemper et al., 2023), which affects ocean-shelf transport, e.g. through accelerating slope currents by increased along-slope density gradients and reduces upper ocean nutrients and the concentration of these advected on-shelf, e.g. by reducing their resupply by open-ocean deep winter convection (Mathis et al., 2019).

Shelf sea circulation and ocean-shelf exchange control the material property distribution in shelf seas across a range of scales and a variety of processes (Huthnance, 1995). They are driven by wind and buoyancy forcing and include tidal residuals. Each of these is impacted by climate change and in some cases dramatic modifications in circulation are projected (Holt et al., 2018). This potentially leads to substantial changes in biogeochemistry (Galli et al., 2024; Wakelin et al., 2020).

Shifting ocean boundary currents provide a dynamic link between the open and coastal ocean, mediating property exchange between the two. In all ocean basins, the intensification and/or shift of western boundary currents (Yang et al., 2016) can result in a rapid "tropicalization" of temperate regions (Wu et al., 2012). For example, the acceleration of the East Australian Current leads to one of the strongest warming hotspots, reaching 0.4 °C per decade from 1982 to 2016 in the Tasman Sea (Shears and Bowen, 2017). This in turn impacts marine ecosystems, e.g. with many fish species extending their southern range, and with the arrival of invasive species and the loss of endemic ecosystems (Robinson et al., 2015).

Upwelling is generally expected to intensify under future climate heating as the land is expected to warm faster than the ocean, which will strengthen atmospheric pressure gradients and intensify alongshore winds (Bakun, 1990). ESMs generally project changes in wind patterns that drive an increase in upwelling in the eastern boundary upwelling systems' poleward regions and a weakening in equatorward regions (Bograd et al., 2023). Such changes will affect the transport of deep ocean water into the coastal ocean. This water is high in nutrients, low oxygen and pH, and so influences primary production and the wider ecosystems in the coastal ocean. Competing processes lead to extensive uncertainty on the effects of climate change in upwelling systems (Pozo Buil et al., 2021), e.g. due to changing source water composition (Rykaczewski and Dunne, 2010) and the depth of upwelling.

Global sea level rise results from the thermal expansion of the ocean, land ice mass loss from mountain glaciers and ice sheets, and changes in land water storage (Fox-Kemper et al., 2023). Regional sea level rise (relative to land movement) deviates substantially from this global mean (e.g. Palmer et al., 2020) due to the redistribution of heat, salt and mass in the ocean by circulation and the redistribution of land-based ice and water, among other effects (Woodworth et al., 2019). Moreover, the frequency of coastal flooding events (e.g. from storm surges) is substantially increased by large-scale sea level rise (Jevrejeva et al., 2023). Regional Sea Level Rise Assessment Reports highlight the need for climate coastal downscaling to interface with policy makers for adaptation planning (van den Hurk et al., 2024).

Storm surges and extreme waves are significant causes of coastal flooding. They are driven by the winds and, to a lesser extent, pressure associated with storm systems. On open shelf seas storm surges largely follow long-wave rotational dynamics (i.e. Kelvin waves) with frictional effects increasingly important in shoaling water. As the coast is approached, resonance, tide-surge interaction and other non-linear effects can become important (Olbert et al., 2013) and restricted flow through narrow channels into isolated basins may also have local-to-regional effects (Olbert and Hartnett, 2010).

Reduced sea ice cover will increase the exposure of high latitude coastal oceans to wind forcing, increase light availability through the water column, increase air-sea gas exchange and increase exposure of coasts to wave effects. Consequent ocean spin up (Muilwijk et al., 2024) leads to increased mixing, potentially mixing up of warmer water to the base of the ice, further accelerating sea ice loss (Rippeth and Fine, 2022).

Ocean acidification results from the continuous increase of atmospheric CO_2, increased oceanic uptake of CO_2 and consequent decrease in oceanic pH and carbonate ions. Ocean acidification has been observed to impact at both an organism and ecosystem level (Doney et al., 2020); the magnitude of the impact strongly depends on the ecosystem, its resilience and the intensity of the other stressors (e.g. warming and eutrophication). Important interactions have emerged with other stressors including, most notably, harmful algal blooms (HABs) and temperature, with studies suggesting acidification and warming may promote growth and toxin production in HABs (Brandenburg et al., 2019).

Deoxygenation is manifest in the global coastal ocean (0–30 km from the coast) as the oxygen inventory here has been declining on average by -0.28 $\mu molL^{-1}yr^{-1}$ over 1976–2000 (Gilbert et al., 2010). This change is driven by warming decreasing oxygen solubility, by changes in ecosystem productivity and phenology, altering oxygen production and consumption, and by changes to vertical and lateral transport. In the coastal ocean, the oxygen state is also modified by interaction with terrestrial nutrient input and consequent eutrophication, benthic processes, and circulation (e.g. upwelling of low oxygen water) and mixing (e.g. whole water column ventilation) patterns (Breitburg et al., 2018).

Biological productivity is central to marine ecosystem health. Globally, net primary production is generally projected to decline due to reduced vertical nutrient fluxes resulting from increased stratification. However, there is a high degree of variability across regions and models, with both positive and negative trends being projected. This variability arises from the delicate balance of processes controlling primary production (light and nutrient limitation, temperature dependent recycling, zooplankton grazing etc), and the variability is seen to increase from CMIP5 to CMIP6 (Kwiatkowski et al., 2020). This uncertainty is amplified in the coastal ocean as further processes are introduced, e.g. ocean-shelf transport, riverine nutrient inputs and benthic exchange (Holt et al., 2012; Holt et al., 2016). Hence, the sign of change in primary production is highly context dependent. This in turn leads to highly variable changes in zooplankton productivity; there is evidence of trophic amplification, i.e. both positive and negative relative changes in secondary production are greater than the corresponding change in primary production (e.g. Chust et al., 2014). Changes in productivity at higher trophic levels are subject to bottom-up climatic controls as well as changes at a species level and at a food web/ecosystem level. For wild capture fisheries, fishing pressure and hence, fisheries management practices, also impact productivity.

Coastal habitats such as seagrass, macroalgae, salt marshes, mangroves and corals are economically and ecologically valuable; they contribute to primary production, are the foundation for complex food chains and serve as habitats for many invertebrates and juvenile fish (Fulton et al., 2019). In many cases they also offer natural protection from coastal hazards and sequester significant amounts of carbon, among many other ecosystem services. They are threatened by stressors such as declining water quality (Baird et al., 2016), rising temperatures and shifts in species competition (e.g. invasive species following changes in ocean circulation and temperature). In many coastal systems, sea level rise is manifest as an inland encroachment of the sea. This often shrinks the space available for near-coastal habitats in a process known as coastal-squeeze. In reef environments, the competition between coral, seagrasses and macroalgae is driven by complex interactions between water quality, cyclone season, and large scale weather drivers, such as ENSO (Holbrook et al., 2020). Climate change leads to an increase in frequency and intensity of stressor events, and so to multiple stressor impacts and the recovery times between disturbances becomes too short for the coral reef to survive (Miller, 2015).

Riverine runoff can change dramatically as a result of both climate-driven changes in catchment precipitation (from the accelerated hydrological cycle) and human water extraction (especially for agricultural purposes). Reduced river flow can lead to increased saltwater intrusion and aquifer salinization (Ferguson and Gleeson, 2012; van de Wal et al., 2024), and also reduced coastal stratification and decreases in local sea level (Verri et al., 2024). Moreover, extreme precipitation events, with accompanying biogeochemical and sediment input, can lead to degradation of coastal ocean water quality and shifts in coastal morphology and erosion patterns.

Upscaling coastal ocean processes to the wider earth system

Climate change impact studies of the coastal ocean also provide insights into the role of ocean margins in global scale change, which is also often poorly represented in ESMs. While they do not necessarily describe the complete interaction with the earth system, regional studies can identify the contribution of different processes and their response to change, and also inform the development of more comprehensive ESMs. Some key processes involved in this upscaling are:

Biogeochemical cycling processes that result in a net transport of carbon from the surface to the deep ocean (the biological carbon pump) have been estimated to contribute to the sequestration of 5–13 PgC yr^{-1} (e.g. Siegel et al., 2014). The coastal ocean is estimated to contribute 0.37–0.59 PgC yr^{-1} of this (Resplandy et al., 2024). While this is a small component (5–7 %) of the global value, it is highly uncertain, highly vulnerable to future change, and generally poorly represented in ESMs. Furthermore, the ocean is a net source of two potent greenhouse gases: nitrous oxide and methane (Resplandy et al., 2024), which offset the carbon uptake via the CO_2 sink (by 30–60 %). Resplandy et al. (2024) compared observed and modelled products and attributed the apparent systematic seasonal offset to the winters in high latitudes, highlighting the contribution of riverine carbon inputs, which are often poorly resolved in ESMs.

Ecological connectivity between different communities can be impacted by climatic changes in shelf-ocean transport, shelf sea circulation and boundary currents noted above, changing the transport of larvae, mixing or isolating genetically different communities and introducing non-native species. This, in combination with shifting ranges of habitability, can have ecological impacts at ocean basin scales (e.g. Kelly et al., 2020).

Ocean-ice sheet interactions play a crucial role in determining mass loss from continental ice sheets, and therefore future sea level rise. Enhanced penetration of warm sub-tropical waters to higher latitudes enhances the likelihood of these warm waters being exchanged onto the continental shelf and then into fjords or other coastal areas where they can enhance the melting of tidewater glaciers (Straneo and Heimbach, 2013).

Dense water formation is a climatically important process in several coastal ocean regions, such as in the Arctic, Southern Ocean and Mediterranean**.** Dense water cascading in coastal and shelf seas e.g. in the Arctic (Luneva et al., 2020), contribute to the formation of deep water masses. These can modify open-ocean convection and contribute the lower limbs of the meridional overturning circulation (Dey et al., 2024). This helps control the distribution of excess (anthropogenic) heat and carbon across the global ocean, and also delivers oxygen to deep waters.

Climate interventions, in the form of net removal of carbon dioxide from the atmosphere, are now required alongside significant decarbonisation of human activity to limit global warming to 2 °C above pre-industrial levels (IPCC, 2023). Accelerating the uptake of carbon dioxide by the ocean (marine Carbon Dioxide Removal; mCDR) is gaining prominence as an option for net negative emissions. Examples include Ocean Alkalinity Enhancement (OAE), which restores the oceans' pH to pre-industrial concentrations and so increases the capacity of oceans to absorb atmospheric CO_2 (Lenton et al., 2018) and carbon sequestration by growing and/or sinking macroalgae (OceanVisions and MBARI, 2022). The practicality and efficacy of the approaches and their wider consequences for the marine environment are highly uncertain.

2. Regions

The regional nature of coastal ocean modelling provides a key challenge to coordination and cross-comparison of downscaling studies. Different organisations and practitioners naturally have different regions of focus driven by end user demand, scientific expertise and resource availability. A global scheme to organise regional downscaling simulations is an important element of a coordinated simulation approach, both for intercomparison and to systematise the assessment of climate change impacts, informing GCO-MIP Strands 1 for cataloguing and assessing existing simulations and 3 for defining standard simulation regions. IPCC-AR6 provides a set of regions for its assessment (Iturbide et al., 2020) including open-ocean and coastal ocean regions. However, these do not provide an attractive scheme for either organising an assessment or defining regional models in the coastal ocean, e.g. the Gulf of Mexico is divided between five regions and two of these include both Atlantic and Pacific coastal seas. Large Marine Ecosystems (LMEs; Fig. 3) provides a scheme for dividing the coastal ocean that is commonly used in ecosystem-based management activities (Kelley and Sherman, 2018) and can form the basis of simulation domains, individually or combined; (Barange et al., 2014; Holt et al., 2009), but the scheme was not designed for this purpose, e.g. there is great disparity between the size of LMEs and many oceanic island states are not included. CORDEX identifies 14 continental scale domains (https://cordex.org/) to be modelled by downscaled regional climate models, and an objective of the CLIVAR-CORDEX-Ocean TF (Section 1.1) is to propose a new set of reference ocean domains suitable for regional ocean climate modelling and assessment.

2.1. Coverage of regional downscaling

As can be seen in Fig. 3, most coastal ocean climate downscaling studies have been carried out for European, North American and East Asian seas, while some regions, such Africa's, South America's, and South and South East Asia's coastal ocean regions have seen no or very few downscaling studies. This also reflects the distribution of the FLAME community. While global models, basin scale models and coordinated multiple regional models (Barange et al., 2014; Holt et al., 2009) can provide more comprehensive coverage and address this patchy nature, it is important that they incorporate local knowledge and regional practitioner participation into the process. This is vital to inform the experiment design and avoid 'parachute science'. While climate science generally relates to the global commons, climate impact studies relate to

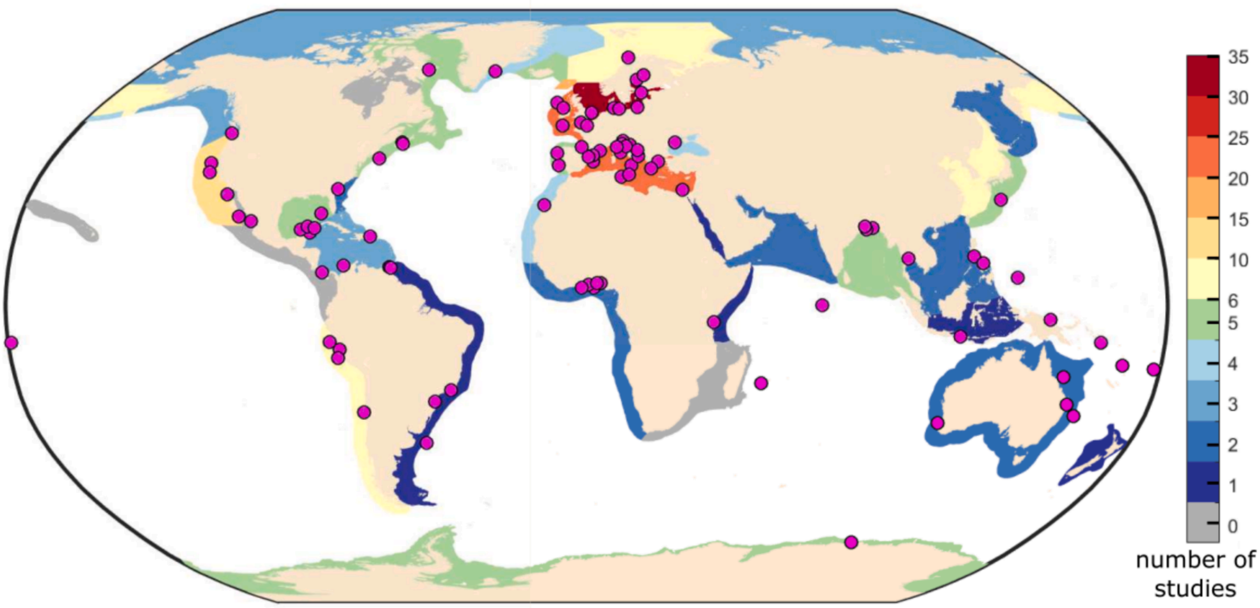

Fig. 3. Indicative number of climate downscaling studies mapped by Large Marine Ecosystem, showing that downscaling studies have a highly patchy distribution. Building a global picture that draws fully on local knowledge requires international partnerships, capacity building and knowledge sharing. The map is based on the list of studies given by Drenkard et al (2021) and Holt et al (2022) and recent updates. Studies are listed in Supplementary Material. With the exception of Liu et al's (2013) study of the Galápagos Archipelago, no 3D dynamical downscaling for oceanic islands outside of LME's was found in this literature review. Circles show the location of the GlobalCoast Experiment Pilot Sites identified in a survey in 2023 that identify climate change as a priority challenge (https://www.coastpredict.org/globalcoast/).

diverse regional and local interests, value systems and cultures, all of which need to be taken into account.

A scheme of regional models for global coastal ocean coverage might be expected to have 20–50 regions, e.g. Holt et al (2009) used 42 regions based on LMEs, and it is realistic that such a scheme could (and should) include an element of end-users co-design and local practitioner engagement. However, a scheme for global coverage at sub-regional and local scales (defined below) would require 100 s-1000 s of regions and this local engagement becomes generally impractical. An alternative for these finer scales is to use a combination of an end-user/local practitioner led approach and a case study approach. To initiate this, CoastPredict conducted a survey in 2023 of coastal pilot sites for a GlobalCoast Experiment, receiving 130 responses from 66 countries (https://www.coastpredict.org/globalcoast/; the survey is due to be re-opened in 2025). Of these 90 pilot sites, shown on Fig. 3, identified "Support adaptation to, and mitigation of, impacts of climate change on coasts…" and/or "Minimise climate and shorter term impacts on morphodynamics.." as a priority in the survey. To facility the development of regional and local capacity to meet these needs requires well defined case studies to provide 'worked examples', and this in turn requires an approach to regional classification to systematically build a set of exemplar case studies (GCO-MIP Strand 3).

2.2. Regional classification

An ability to systematically classify coastal ocean regions based upon their hydrodynamic, biogeochemical, ecological and morphodynamical processes, and also geographic setting, is an important step towards achieving global coastal resilience. A particular motivation is to identify groups of regions that adequately cover contrasting responses in each context, and so build a representative set of case studies (for GCO-MIP Strand 3). Moreover, classification schemes facilitate the transfer of knowledge and methodologies from well-studied regions to less studied regions, e.g. sharing modelling best practice between regions where similar approaches are applicable. Classification can be based on dominant processes, geography and/or societal drivers.

Process-based and geographic classification

This identifies regions with a common internal balance of forces and/or common large scale climatic drivers, alongside geographic characteristics such as basin size, shelf-width, and inter-basin connectivity. This is context dependent as it potentially spans hydrodynamics, biogeochemistry and ecosystems. Robinson and Brink (2006) provide a classification scheme based upon geographic location (polar, subpolar, tropical), eastern versus western boundary settings and a region's connection to land (e.g. semi-enclosed seas, wide versus narrow shelf). This could be usefully extended to include processes and drivers. For barotropic processes, it might consider areas impacted by storm surges versus extreme waves, and the driving meteorology (e.g. hurricanes, extratropical cyclones, etc). For example, Rueda et al (2017) build a global coastal flooding classification based on tides, storm surges, waves and mean sea level. For baroclinic processes and circulation, a scheme could be based on temperature versus salinity stratification, mixing regime (permanently versus seasonally stratified or well mixed), ocean-shelf exchange characteristics (upwelling versus downwelling), residence times (Liu et al., 2019) and shelf-connectivity (Popova et al., 2019). Much progress has been made in classifying global marine ecological provinces, underpinned by satellite remote sensing (Kavanaugh et al., 2016; Longhurst, 1998; Oliver and Irwin, 2008) and increasingly drawing on 3D hydrodynamic-ecosystem models (Sonnewald et al., 2020). This could be tailored to the coastal ocean, focusing on the estuarine to shelf-break transition zone and taking into consideration coastal habitat classifications and small-scale hydrodynamics.

Near-shore, coastal and urban classification

A nearshore coastal classification might include: deltas, tidal systems, lagoons, fjords, large rivers, karstic coasts and arheic coasts (Dürr et al., 2011). Sayre et al. (2021) propose a global classification of about 4 million 1 km coastal segments, using 10 variables that represent key characteristics of the coast, encompassing adjacent sea, land and coastlines attributes. Urban settlements profoundly modify coastal dynamics, through the built environment, and climate change increases the exposure and the vulnerability of the population of these settlements. They are major sources of pollution and other direct anthropogenic impacts acting along-side climate change. Hence, directly accounting for the *Urban Ocean* in any classification approach is crucial. Coastal and urban classification needs to be coupled to the process-based, geographic and/or societal classification approaches for wider coastal ocean areas.

Societal classification

This is based on issues of greatest societal concern, and subdivisions therein. For example, coastal flooding and erosion from sea level rise, surges and/or extreme waves; sustainable use of living marine resources; water quality and health hazards; and risks to other ecosystem services (e.g. cultural amenity) and intrinsic ecosystem value, etc. This identifies collections of regions where a particular challenge is most pressing and also areas of compound risk, and naturally builds on the hazard-exposure-vulnerability IPCC risk framework (IPCC, 2014). It should go beyond macroeconomic and demographic factors to include impact on culture and ways of life, e.g. indigenous coastal communities. These can then be studied collectively to aid cross fertilisation of ideas and solutions.

3. Model choices

Future climate information in the coastal ocean can be derived from several classes of dynamical models (illustrated in Fig. 4), particularly characterised by how the ocean models are forced by ESM data and the degree of interactive coupling:

- Direct use of ESMs (Fig. 4a)
- Global ocean models forced by an ESM (Fig. 4b)
- Regional ocean models forced by an ESM (Fig. 4c)
- Regional ocean models forced by an ESM with oceanic downscaling (Fig. 4d)
- Regional ocean models forced by an ESM with atmospheric downscaling (Fig. 4e)
- Regional ocean models forced by an ESM with oceanic and atmospheric downscaling (Fig. 4f)
- Regional ocean–atmosphere coupled models (Fig. 4g)
- Global ocean models forced by an ESM and regional atmospheric downscaling (Fig. 4h)

The diversity of approaches employed reflects both the complexity of the problem and the wide range of societal challenges that need to be addressed. In navigating the multitude of model choices, there is a well-known tri-axis of modelling resource allocation: resolution versus complexity versus simulation length or ensemble size. This tension is usually considered in terms of computational resource, but is mirrored in the practitioner and data storage resource required, often more costly factors. Another consideration is the balance between general simulations with a wide range of applications versus highly specific ones targeted at a single challenge. Finally, there is sometimes a balance is between explanatory and predictive power (see particularly Section 3.6). Crossing these considerations are issues of scale. It is helpful to group the represented scales in four classes (Fig. 5): Global (10–100 km; current state-of-the-art horizontal resolution); Regional (5–10 km); Sub-regional (1–5 km); and Local (50 m-1 km). These form guideline scales for GCO-MIP Strand 3. Beyond this is the ‘urban’ scale (1 m-50 m) required to directly represent individual built structures, which has received little attention as it is extremely computationally challenging, but is critical for understanding direct impacts in many contexts. *Urban oceanography* has begun to establish the foundational principles for modelling these critical environments (Blumberg and Bruno, 2018), but despite the critical relevance of this scale for societal impacts, no climate downscaling has yet been conducted.

Adopting a model (or suite of models) requires substantial

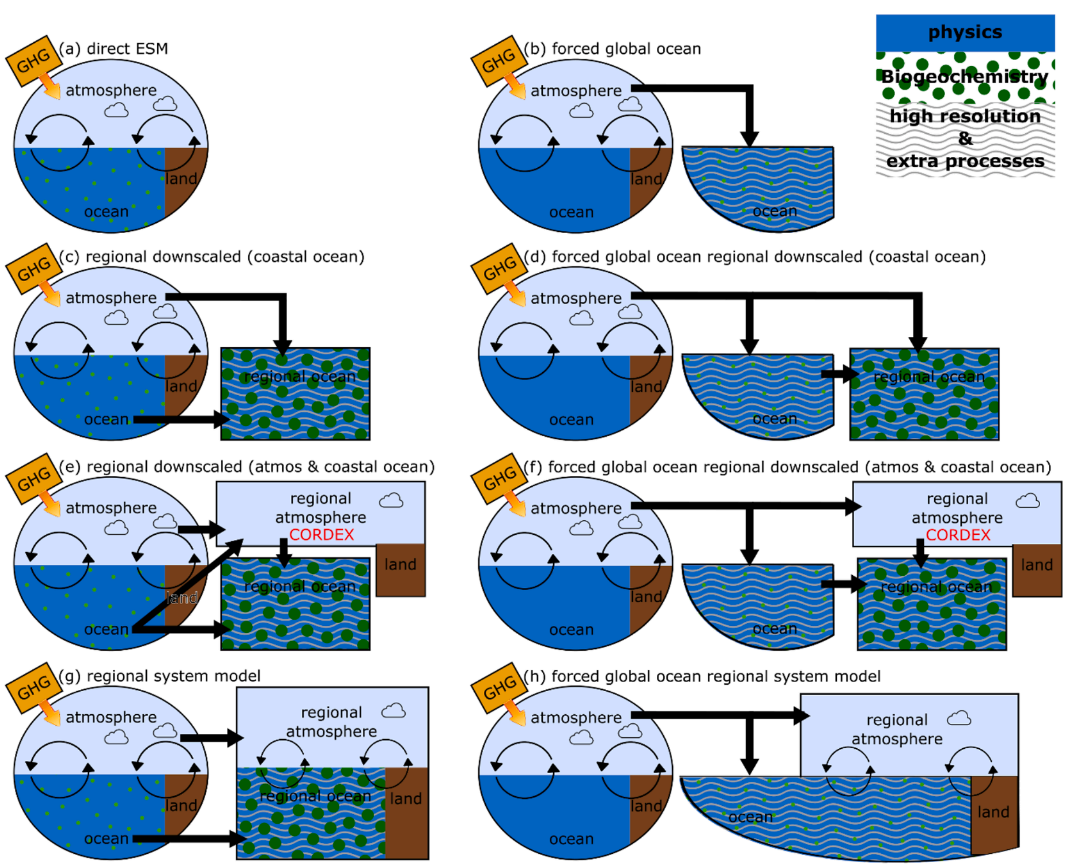

Fig. 4. Schematic of the various downscaling modelling approaches.

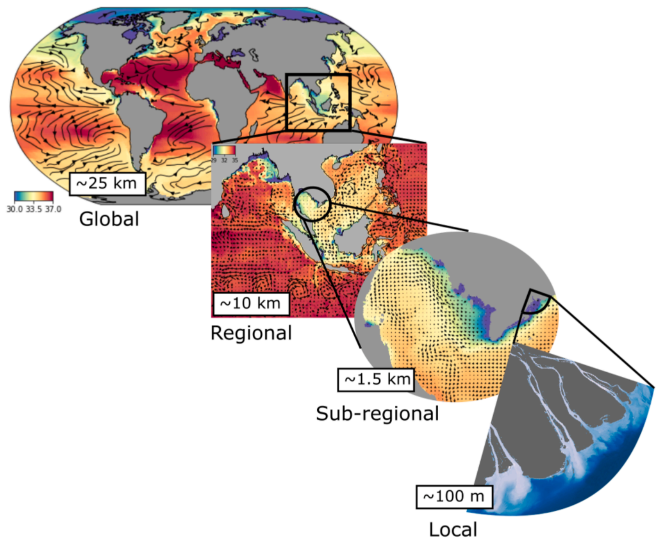

Fig. 5. A cascade of scales: stepping through scales allows locally relevant climate information to be provided, but modelling constraints (e.g. timesteps) make the highest resolutions very expensive for multi-decadal simulations.

institutional and individual investment, often with multiple contrasting applications to consider; for a large research or operational centre this can be a once in a decade (or longer) decision. So, while we lay out many options below, it is rarely the case that they can be freely selected without wider restrictions. On that basis, a diversity of approaches beyond what might be considered "ideal" must be embraced. In Section 6 (Table 1 and 2) we summarise these options in terms of how they relate to the current state-of-the-art.

3.1. Global models

While much attention has been given to regional downscaling (see below) for investigations of climate impacts in the coastal ocean, global models retain an important role. Dynamical downscaling is expensive and time consuming, and there is a wealth of ESM data available from CMIP repositories. So in many contexts direct use of global models is the most practical (or only) option. For example, investigations of climate change impacts on the hydrodynamics of seas around small oceanic islands have almost exclusively used ESMs.

As global models develop, with improved resolution and process representation, their fidelity in the coastal ocean is expected to improve and they are set to become an increasingly important tool for this challenge, particularly at the regional scale. They overcome the issues of dynamical consistency and lateral boundary conditions that hamper regional models, and naturally encompass the upscaling processes identified in Section 2. Global forced ocean models used for research and operational oceanography at multidecadal timescales have typical resolutions of 1/4°–1/10° (25 km–10 km), as do the coupled models of HighResMIP. For example, Kelly et al (2025) consider future climate change in North Atlantic ecosystems in a forced global model at 1/12°. This passes a minimal acceptable resolution for many coastal ocean applications (Holt et al., 2017), and so can be used for some investigations of coastal ocean climate impacts, although not yet at the sub-regional or local scales (Fig. 5). In addition to refined resolution, global ocean models forced by the output of ESMs (Fig. 4b) have the advantage (over direct use of ESMs; Fig. 4a) of potentially improved process representation (e.g. coupling to more sophisticated marine ecosystem models or addition of shelf sea physics). They also allow a reduction in the biases often apparent in ESMs after multi-centennial spin-up (Yool et al., 2020). These benefits are offset by the lack of ocean-ice-atmosphere dynamical consistency; the forcing atmosphere has experienced different underlying ocean-ice conditions. This inconsistency is manifest in centennial scale adjustment (or drift), which needs to be carefully accounted for in the analysis of climate trends, e.g. by using a control run. While kilometre scale global models are emerging (Uchida et al., 2022), resolutions finer than ~1/10° are not currently practical for global climate timescale integrations (particularly coupled to marine ecosystems and/or ensembles), and require approaches for multiscale global modelling and regional downscaling. Global structured quadrilateral mesh models can achieve resolution refinement by rotating the grid pole over a region of interest (Mayer et al., 2022; Sein et al., 2024). Unstructured grid models and adaptive refinement, based on triangular (e.g. FESOM; Semmler et al., 2020) or hexagonal (e.g. MPAS; Hoch et al., 2020) meshes, enable a seamless integration of the coastal ocean into Earth Systems Modelling (Mathis et al., 2022). While this provides a consistent two-way coupling of cross-shelf exchange, the approach introduces some methodological challenges: parameterisations need to be scale-dependent and can no longer be tailored to the characteristics of individual regions.

Alongside full-physics global ocean models, depth-averaged (2D) models focus on the water levels and currents that arise from tides and meteorological forcing, but exclude a representation of the 3D currents and hydrography. Such models are forced with winds and atmospheric pressure from climate models to estimate how storm surges might change in future climates (Muis et al., 2020; Vousdoukas et al., 2018), and are a particular example of challenge-specific models (as distinct from generic models). Mean sea level changes (from ESMs) can be incorporated to consider their effects on both extreme sea levels and tides (Pickering et al., 2017). Such investigations are highly suited to multiscale approaches, e.g. with triangular unstructured meshes, to refine resolution as the coast is approached.

Including global models in GCO-MIP will improve prediction robustness and constrain uncertainties in both global and regional approaches, and also form important connections between these disparate communities. For example, high-resolution regional models can help identify biases and the most relevant missing processes in global models, whereas global simulations allow quantification of regional model errors that relate to missing connectivity and large-scale embedding, and can also provide improved boundary conditions over the direct use of ESMs (GCO-MIP Strands 2 and 3).

3.2. Regional modelling

Forcing regional models with output from ESMs (regional downscaling) is the common approach to providing improved climate impact information in the coastal ocean. The regional models can be ocean-only (Fig. 4c, d, e, –f) or ocean–atmosphere coupled (Fig. 4g), including sea ice and waves as needed, and draw heavily on the models used widely in operational and research oceanography (Polton et al., 2023). Regional modelling decouples downscaling from the global climate modelling effort adding a high degree of efficiency and flexibility to the model choices, enabling freedom to make choices that would otherwise substantially degrade the simulation globally. Moreover, a single ESM can support many regional models that were not conceived before the ESM was run.

There are many readily available coastal ocean models that can be applied to climate downscaling, for example ROMS (e.g. Pozo Buil et al., 2021), NEMO (e.g. Wakelin et al., 2020) and MOM6 (e.g. Ross et al., 2023) among several others. Objectively testing one model's skill against another is difficult and costly, and the selection is usually based on pragmatic grounds and the model's track record in a specific context. That said, model structural uncertainty (see below) is a key aspect in future climate downscaling studies that is often overlooked. Hence as much as in CMIP, model diversity is a crucial aspect of regional marine climate downscaling.

The scale of regional models is a pivotal factor that governs the level of detail and accuracy they can provide in understanding and projecting climate dynamics in specific areas. It determines the model's ability to capture fine-scale features, such as coastal geography and local dynamical processes. Fine-scale regional models, with a resolution of hundreds of metres to a few kilometres (local, sub-regional), can capture local coastal features, such as bays, estuaries, and small islands, and better resolve dynamic processes, e.g. river plumes. Coarser-scale regional models, (typically 5–25 km) allow for longer simulations and are often acceptable for open shelf sea cases but have limited applicability in near coastal regions. See Holt et al (2017) for a discussion on the scales of coastal ocean processes and how they are represented by different ocean model resolution. Nesting and/or unstructured grid models can cross these scales.

Model horizontal and vertical resolution is a key determinant of the computational requirement of a set of experiments. Alongside resolution is area covered, determined by the application and some guiding principles noted by Polton et al. (2023). However, model timestep becomes a critical issue at fine resolution (km and less), in models with an explicit time-stepping scheme. Since, with current MPI parallel computing approaches, refining resolution cannot be offset by simply increasing the computer core count to maintain a constant turn-around time (Simulated Years Per Day; SYPD), as can be done with expanding the area covered. For example, the 1.5 km NW European shelf model (Lewis et al., 2019) has approximately the same number of 3D ocean grid cells as a ¼° global ocean model (e.g as in the ESM HadGEM-GC3.1-MM; Storkey et al., 2018) (10^8 versus 1.3×10^8), but requires a $\sim$ 17 times smaller time step (80 s versus 1350 s), so will generally achieve roughly $\times$ 13 fewer SYPD on the same core count. This is off-set by the required spin-up time being much less (Section 4.2), and compounded by the disparity of computer resources often available for regional versus global studies. The computational challenge leads to the hierarchy of scales and areas covered noted above (Fig. 5); it is currently not practical to model large regions at kilometre and sub-kilometre resolution, for climate time scale and spanning aspects of uncertainty (see below), and so a trade-off is generally needed. Hence, a large majority of downscaling studies are carried out at the regional (5–25 km) scale; of the $\sim$250 studies listed the Supplementary Material (as used in Fig. 3), only 17 are at the sub-regional scale (1–5 km) and 8 at sub-km scale.

Regional climate models: air-sea coupling

A key question on the model complexity resource-axis is whether to use a forced ocean or a coupled Regional Climate Model (RCM). RCM's are limited area coupled ocean–atmosphere (−sea ice) models, forced by output from ESMs, and can include all the processes commonly included in ESMs (Giorgi, 2019). The choice of domain is crucial in determining what processes will be forced by the parent model or evolve freely within the higher-resolution regional domain. Questions of scale, in both ocean and atmosphere, noted above apply equally to the RCM case. As a specific example, the Mediterranean Coordinated Regional Downscaling Experiment (Med-CORDEX) pioneered regional coupled climate modelling, extending to biogeochemical processes (Ruti et al., 2016), developing standard output that can be easily used by different impacts-modelling communities (https://www.medcordex.eu/references.php). All the models include interactive rivers (covering the whole Mediterranean catchment). In an adaptation to the rotated-pole forced global ocean case described above, a global ocean model is dynamically O-A coupled only over the region of interest and ESM forced otherwise (Fig. 4h), e.g. downscaling atmospheric conditions in Northern Indian Ocean (Sein et al., 2024), NW Europe (Mayer et al., 2022) and East China Sea (Hao et al., 2024). Each of these cases include a continental scale atmospheric downscaling domain and regional to basin scale ocean grid refinement.

The advantages of regional O-A coupling have been known for many years (e.g. Schrum et al., 2003) but none-the-less the vast majority of coastal ocean modelling studies use a prescribed atmospheric forcing. O-A coupled models are complex and expensive, multiplying the required computational and practitioner resource, and they also require cross-sectoral expertise. Together this provides a substantial barrier-to-entry for regional coupled simulations. The implicit scientific justification for not using O-A coupling is that atmospheric spatial scales are much larger and temporal scale much faster than for the ocean, so weather propagates into the region of interest from elsewhere. The validity of this scientific justification can only be definitively established using experiments with a fully O-A coupled system; an expensive test that is rarely conducted (e.g. Lewis et al., 2019).

A natural advantage of O-A coupling is the provision of consistent high resolution atmospheric forcing, alleviating the need to otherwise source or generate this. O-A coupling instead gives freedom to choose an appropriate atmospheric resolution for the ocean region in question. Local climate, weather patterns and extreme events can be significantly impacted by O-A coupling. The coupling between sea surface temperatures and atmospheric circulation can lead to the improvement in the representation of monsoon systems and seasonal storms, tropical cyclones and hurricanes, and storm surges and coastal flooding during severe weather events (e.g. Somot et al., 2008). Moreover, O-A coupling can improve the temporal and spatial distributions of SST, stratification and density driven currents (Gröger et al., 2021), significantly affect atmospheric processes relating to high-impact events (Meredith et al., 2015; Senatore et al., 2020) and also the stability of the atmospheric boundary layer, the thermodynamics and dynamics feedbacks, and interactions involving oceanic mesoscale features (e.g. Renault et al., 2017). Similarly marine heatwaves can be sustained through positive O-A feedback, where the warm sea surface temperatures reduce cloud cover (Berthou et al., 2024). These in turns can influence land-temperatures with direct societal impacts. Close to the coast O-A coupling becomes important when considering, for example, the phase lag between diurnal SST and related turbulent heat fluxes (Zhao and Nasuno, 2020) and changes in currents linked to tidal cycles and wind speed (Renault and Marchesiello, 2022).

The importance of including surface waves in an O-A coupled simulation depends on the context. When modelling fast moving systems such as tropical cyclones, including surface waves in O-A coupling allows the interactive exchange of energy and momentum between the systems as the cyclone passes over the ocean and has been shown to improve performance compared to uncoupled models (Castillo et al., 2022; Lok et al., 2022). Care is needed as the influence of O-A coupling is not always beneficial, e.g. when component biases reinforce each other. This highlights the need to bring together balanced sectoral expertise in developing any coupled system.

Land-Sea coupling

Terrestrial input is a key aspect of coastal ocean modelling, in terms of fluxes of freshwater, heat and biogeochemical constituents, and the variability of these fluxes on timescales from extreme events to long-term secular change. Land-based pollutants are also a critical issue, but not considered further here. The focus is usually on rivers, via estuaries and deltas, but groundwater (Luijendijk et al., 2020) and ice sheet melt provide more diffuse sources, important in some cases.

Riverine inputs to coastal ocean models can be based either on observational climatologies or hydrological/land surface models. While some countries comprehensively monitor riverine discharge, most of the world's rivers are not gauged, and where they are, discharge measurements are often far up-stream from the river mouth and sampled at low frequently. Measurements of riverine biogeochemical properties (e.g. macronutrients) are even more scarce. To generate observation based forcing, future change has to be estimated, e.g. by relation to local precipitation changes. Riverine inputs based on hydrological model outputs are more comprehensive but include their own uncertainties and biases (e.g. Coxon et al., 2019). Hence, there is significant uncertainty in simulating both present day runoff impacts and future scenarios. This points to the need for a much-improved dialogue between hydrological/land surface modellers and coastal ocean modellers. Several studies have shown realistic temporal variation of river discharges (as distinct from the seasonal climatologies often used) influences the hydrodynamics (e.g. salinity and sea level) and biochemistry across different time scales (e.g. Dandapat et al., 2020;

Piecuch et al., 2018; Verri et al., 2024).

River-sea interactions are often seen as a one-way connection from land to sea. However, there are several significant interactions in the other direction. A notable example is coastal flooding, and particularly compound flooding in estuaries where storm surge water levels and wave setup can exacerbate fluvial and pluvial flooding (Lyddon et al., 2024). Salinization of coastal aquifers is an urgent issue that necessitates new modelling approaches in climate downscaling (Ferguson and Gleeson, 2012; van de Wal et al., 2024). Moreover, there are impacts of the coastal ocean on local atmospheric processes, and then on the land. These direct us to interactive coupling with land surface and/or hydrological systems in some contexts (e.g. Feng et al., 2024).

The integration of hydrological models into RCMs provides a self-consistent local water cycle. For example, limited area climate downscaling in the AdriaClim project, has modelled about 145 catchments discharging into the Adriatic Sea, finding that the projected decrease in runoff acts in the opposite direction to the global warming in the Northern Adriatic sub-basin by weakening the density stratification, increasing the dense water formation and reducing the total sea level rise (Verri et al., 2024).

Future runoff will depend on complex interactions between rainfall, land use and demographic scenarios, dependent on both societal and climatic factors. For example, in the Baltic Sea, biogeochemical projections of a range of nutrient load scenarios based on present use and the regional convention on marine environmental protection (HELCOM) showed a large spread in future bottom oxygen conditions depending on the combination of climate change and land use/nutrient abatement scenario (Saraiva et al., 2019a). For CMIP6 scenarios, it is possible to generate regional nutrient loads that are consistent with the global socioeconomic pathways of the various scenarios, but this is highly challenging. Global and regional land nutrient flux models (e.g. IMAGE-GNM; Beusen et al., 2022) provide a solution, but again a much-improved dialogue between the communities is required to provide the necessary fluxes and appropriate spatiotemporal resolution.

3.3. Biogeochemistry and ecosystem modelling

Models of marine biogeochemistry and lower trophic level ecosystems are a central element to many coastal ocean climate impact investigations. The biogeochemical models are forced (offline or online) with ocean circulation models, which provide the advective and diffusive transport and physical environmental conditions (e.g. temperature and salinity).

At the core of each biogeochemical ecosystem model is the cycling of key elements (usually carbon and one or more nutrients, N, P, Si, Fe), functional lower trophic groups (i.e. plankton), non-living organic matter, dissolved gasses, and the inorganic carbon system. The lower trophic levels of the ecosystem are usually represented by a small number of functional groups (e.g. autotrophs vs heterotrophs). Different regions often require different components of the ecosystem to be prioritised, but this must be tensioned against both computation expense and any added uncertainty of including poorly understood processes. For example, at high latitudes they may also consider sympagic (within the sea ice) components, whereas in some seas nitrogen fixers are important. The flexibility to regionally tailor the model is a key distinction between biogeochemical models in the coastal ocean and those used in ESMs, although there is much cross-over between the two.

Biogeochemical modelling

Coastal ocean processes alter fluxes of greenhouse gases and the cycling of carbon, modifying the coastal ocean climate signal for these (Mathis et al., 2024; Pilcher et al., 2022; Resplandy et al., 2024; Siedlecki et al., 2021). The potential influence of the coastal ocean on global climate through the modification of these fluxes has long been suggested, but we are only now developing the capability to explore this quantitatively through improved global and regional models.

Regional simulations dynamically downscaled from ESMs have identified that the inclusion of coastal ocean processes modify global rates of change of carbon variables, particularly subsurface trends (Pilcher et al., 2022; Siedlecki et al., 2021). Downscaled projections that resolve shelf seas simulate trends in variables such as aragonite saturation state and pH that are consistent with those in ESMs, but often differ in magnitude.

Recently, a global model integrated the coastal ocean carbon cycle into the global ocean through regional grid refinement and enhanced process representation (ICON-coast; Mathis et al., 2022). This was able to simulate the observed increase in coastal ocean CO_2 uptake over 1900–2010 (Mathis et al., 2024). By decomposing the drivers of this increased carbon sink, they found that biological process responses to climate-induced changes in circulation in combination with increased riverine nutrient loads together exceeded the solubility pump. Notably, ICON-Coast includes tidal currents, explicitly accounts for sediment resuspension, temperature-dependent remineralization and dissolution in the water column and sediment, riverine matter fluxes from land including terrestrial organic carbon, and variable sinking speed of aggregated particulate matter.

The land-sea interface is also critical for other aspects of the carbon cycle. Analyses of global alkalinity budgets suggest an imbalance may exist, and several hypotheses have been suggested to address this (Middelburg et al., 2020), largely concerning the coastal ocean. Specifically, the riverine fluxes of Particulate Inorganic Carbon could balance the global budget, or the estimates of calcium carbonate burial on shelves could be overestimated. This burial, as well as the coastal ocean cycling of alkalinity from remineralization, is currently missing from global simulations. The cycling of alkalinity has been improved between CMIP5 and CMIP6 in ESMs, but the reason for this improvement is less clear. Without a constrained alkalinity cycle, future projections of the impact of ocean acidification on the carbonate pump, and in turn on ocean carbon uptake, is potentially underestimated (Planchat et al., 2023). Progress requires additional observations in coastal regions, and also consensus on how key processes (e.g. calcium carbonate cycling and sedimentary fluxes) are parameterized.

Lower trophic level ecosystem models

The number of functional types included in an ecosystem model and their ability to respond to external drivers vary from model to model but is in any case very limited compared to the diversity in the real ocean (Fennel et al., 2022). Computational constraints on the number of modelled tracers have led to quite draconian choices on the number of functional types. While significant changes have been made in various ESMs between CMIP5 and CMIP6 (Séférian et al., 2020), their structure is still limited. For example, the representation of key aspects of plankton physiology (e.g. variable multi-nutrient stoichiometry and variable assimilation efficiency for zooplankton) are limited and some key functional groups (e.g. calcifying plankton and diazotrophs) are only occasionally explicitly included, and other processes are absent or overly simplified (e.g. benthic processes, and transformation of terrigenous Dissolved Organic Carbon; tDOC). Kwiatkowski et al. (2018) showed that while the inclusion of variable stoichiometry in phytoplankton did not significantly change the estimates of ocean carbon uptake (between 0.5 % and 3.5 %), much more significant changes were projected in the phytoplankton community composition (with picophytoplankton being less affected) and a strong decrease in food quality in the oligotrophic gyres. Furthermore, variable stoichiometry is crucial to assess the impact of ocean acidification on phytoplankton productivity; Artioli et al. (2014) showed how the extra productivity associated with the increase in carbon uptake compared to nutrient could significantly mitigate the projected reduction in primary production due to increased stratification and the consequent reduction in nutrient availability. Powley et al. (2024) included a detailed model simulating the fate of tDOC of different lability and estimated that modelling the processing of tDOC leads to a reduced uptake of atmospheric CO_2.

Current ecosystem models tend to be quite “rigid” (e.g. fixed structure and parameter set) and this might limit their ability to properly represent key aspects of future climate impacts. For instance, several studies have shown how going beyond a clear separation between autotrophic phytoplankton and heterotrophic zooplankton by explicitly including mixotrophy has important consequences on the cycling of carbon and the transfer of energy across the food web (e.g. Mitra et al., 2014; Ward and Follows, 2016). Despite their relevance, implementation of mixotrophy in a 3D context has been very limited. Besides the computational challenges these models imply, is a lack of comprehensive data on mixotroph characteristics.

A key area of future research in lower trophic level climate projections involves new ways of calibrating biogeochemical model parameters using historical observational data. Kern et al. (2024) employs an advanced machine learning approach to estimate parameters within a pelagic biochemical model containing 17 state-variables and 51 parameters, demonstrating improved alignment with data through local parameter calibration. Including aspects of structural uncertainty in regional and local downscaling model configuration and calibration (i.e. exploring both state-variable choice and parameter sets) is crucial for building comprehensive uncertainty assessments and for cross-regional transferability of biogeochemical models.

Similarly, while there is clear evidence of the ability of phytoplankton to adapt in an evolutionary sense to changing environmental conditions (Irwin et al., 2015) and the importance of adaptation in determining the impact of climate change has been demonstrated in some modelling studies (e.g. Flynn and Skibinski, 2020), these development have yet to be widely adopted.

Benthic habitats house many important ecosystems and support a large portion of living marine resources and other ecosystem services. Despite their importance to a wide range societal challenges, their representation in downscaled models is often highly simplified or absent altogether. The inclusion of a benthic component in ecosystem models is also important for accurate predictions of water column processes, such as nutrient recycling.

Regionally downscaled hydrodynamic-ecosystem models typically have more flexibility on model components than global models and so are used to test these developments, being computationally cheap compared to ESMs. However, the need to explore finer spatial scales on decadal timescales in coastal ocean models, notably at the sub-regional and local scales, imposes new constraints along the “complexity” axis of resource allocation.

3.4. Near coastal modelling

The near coastal zone (a few kilometres from shore) requires special consideration for marine climate impact studies. On one hand, it is highly dynamically complex and computationally demanding (due to fine process and geographic scales) and, on the other, it is arguably the most important, being where society most directly interacts with the marine environment. The substantial change in scales from the current generation of ESMs to near coastal models (from >25 km to <1 km) implies that either a multiple nested or unstructured mesh modelling approach is required. The choice between these depends on the specific modelling objectives, region of interest, model code expertise of institutes and computational resources. Unstructured mesh models allow a seamless transition across scales and grid flexibility to better represent complex coastlines, but are generally more computationally expensive and often have more difficult numerical properties than quadrilateral meshes (Danilov, 2013). Nested models allow different physical schemes and numerical parameterizations to be employed. Structured grid models benefit from a substantially larger development community. However, they only give a limited representation of complex coastlines. Related to these issues are those of upscaling, where near coastal processes influence the larger-scale coastal ocean and beyond, e.g. river plumes influencing coastal currents. Unstructured mesh models naturally capture this, whilst structured grid models can employ two-way nesting approaches (e.g. AGRIF; Petton et al., 2023) to upscale information and maintain dynamical consistency between nests.

Storm surge modelling

Storm surges can be very well described by two-dimensional vertically integrated models, with appropriate parameterisation of wind stress and bottom friction. Future climate projections with storm surge models are heavily dependent on atmospheric forcing able to capture extreme storms. In coastal regions, coupling between ocean and wave models is needed to account for compound effect of surges, tides and waves on total water levels and complex interactions between the three. Several studies have shown the importance of baroclinic effects for depth-averaged modelling of extreme water level (e.g. Muis et al., 2018; Wang et al., 2022). Moreover, climate change induced sea-level rise can result in changes to coastal slopes, bathymetry and cross-sectional area within straits, which adds to the non-linearity of storm surge dynamics, e.g. resulting in higher water levels at coast (Arns et al., 2017). The change in depth due to sea level rise can also changes the tides (Haigh et al., 2020). In high-latitude regions, it is important to include sea ice coupling as seasonal variability and the long-term decline in sea ice cover will change the surface stress and the water level response to wind forcing (Joyce et al., 2019).

Surface wave modelling

At a regional scale, wave projections are produced from spectral wave models either forced by ESMs (e.g. Lira-Loarca and Besio, 2022) or incorporated as an interactively coupled component of an RCM (Gröger et al., 2021). Wave-current interaction is addressed by coupling with a coastal ocean circulation model. In wave dominated shorelines, their contribution to the total sea level extreme can account for more than half of the maximum total water levels (Serafin et al., 2017); noting an empirical approach is required to estimate this total.

Wave projections often do not account for changes in sea level, whether from tides, storm surges, or long-term sea level rise. Non-linear interactions of sea level with waves can be substantial on macro-tidal and wide continental shelves where shallow-water dynamics prevail. For instance, using regional ocean and wave models covering the northeast Atlantic and European shelf, Chaigneau et al. (2023) reported an increase of up to 40 % in extreme significant wave height by the end of the 21st century mainly due to the combined effect of very large tides and mean sea level rise. It is also crucial to consider the modifications in wave setup when making regional projections and to acknowledge their role in local fluctuations of coastal sea levels, particularly in the context of extreme events (Melet et al., 2020). Wind waves can also impact the surface ocean through sea-state dependent air-sea transfer of momentum and energy (and resulting ocean mixing) and through Stokes drift (Lewis et al., 2019; Staneva et al., 2017).

Sea-level rise and extremes

Extreme sea levels are due to the combination of mean sea level, tides, storm surges and waves (Woodworth et al., 2019). Regional ocean models can refine the patterns of sea level change resulting from the transmission to the coast of open-ocean sea level rise and also land sourced mass addition, in response to climate change and variability (e.g. Chaigneau et al., 2022; Jin et al., 2021; Liu et al., 2016). Projected changes in extreme sea levels are usually studied by adding a projected mean regional relative sea level rise to historical distributions of tides, surges and waves, supposing a stationary wave and surge climate (e.g. Fox-Kemper et al., 2023; Kirezci et al., 2020). However, in the coastal ocean there are complex interactions between mean sea level, surges, tides and waves in determining the total water levels (e.g. Haigh et al., 2020; Jevrejeva et al., 2023; Melet et al., 2020; Vousdoukas et al., 2018). Regional ocean models dynamically downscaling ESMs can project extreme sea levels in which changes in mean sea-level, tides, storm surges, waves, and their non-linear interactions are simulated.

Event-based metre-scale downscaling

Exploring atmospherically driven coastal hazards can require the use of metre-scale atmosphere–ocean-wave models to fully understand potential impacts at the “urban” scale. These are far too costly models to run long simulations and multiple climate scenarios. However, this can be envisioned using modelling suites composed of multiple nested grids in the atmosphere and the ocean (e.g. AdriSC in the Adriatic basin; Denamiel et al., 2019). The selection of extreme events from the driving ESMs is key and can be based on the generation of indices linking the synoptic conditions in the atmosphere to the local extreme events at coastal stations, e.g. as used for detecting convective storms (Gómez-Navarro et al., 2022). For the selected extreme events (including false positives), the ESMs are first downscaled with days- to a week- long kilometre-scale simulations relying on a cascade of nested grids, e.g.15 km to 1 km resolution. Finally, the kilometre-scale simulations showing extreme events (i.e., excluding false positives) are further downscaled with 1 to 3 day-long metre-scale simulations and the targeted coastal hazard assessments for future projections can be derived (Denamiel et al., 2023).

Coastal erosion and sediment transport

Modelling approaches used to project shoreline evolution under a changing climate have significantly improved from deterministic applications of the Bruun rule (see Toimil et al., 2020 for a recent review). Coastal management requires projections that span temporal scales up to multidecadal, centennial, and sometimes multi-centennial horizons. Shoreline change results from the combination of oceanic, terrestrial and atmospheric drivers for which event-scale responses convolve with long-term variability (e.g. climate-ocean oscillations) and long-term trends (e.g. sea level rise). The resulting coastal processes are strongly site and context specific with strong influences of the local geomorphic setting, biological-physical interactions (e.g. Solan et al., 2023), and human interventions.

Shoreline projections need to combine information from different products, often across environmental domains. For example, Vitousek et al. (2017) drive a transect based shoreline model of the southern Californian coast with regional estimates of sea level rise from IPCC AR5 and locally downscaled wave models and Gopikrishna and Deo (2019) drive a sediment transport and shoreline evolution model of Chilika lake on the northeast Indian coast with a spectra wave model forced by a South Asia CORDEX RCM. In contrast Antolínez et al. (2018) uses a combination of statistical and dynamical models to downscale wave climate and drive a Coastal Evolution Model of the Carolinas' coast. Complex coasts with multiple coastal land-forms (e.g. cliffs, dunes, beaches etc) require integrating specific component models in a common framework (Payo et al., 2017). The spatial and temporal scales involved make downscaling approaches particularly challenging, especially for long-term shoreline projections that require transient simulations (Section 4.2). Given the complexity of assessing shoreline change, simplifying assumptions are commonplace, but must be carefully evaluated and communicated clearly to end-users. For example, an unchanged bathymetry would only be valid if short term dynamics are unchanged and in the absence of human intervention. Finally, shoreline projections typically operate downstream of a cascade of increasing uncertainty. The consequence is that the treatment of uncertainty in shoreline projection and coastal erosion models requires careful attention both regarding the methods employed and the communication with end-users.

Sediment transport modelling is critical for understanding and managing water quality and ecological function of coastal environments (e.g. Baird et al., 2021), and informing decision-making to design and maintain infrastructure, restore ecosystems (e.g., salt marshes and mangroves), manage pollution, and to protect valuable coastal regions (e.g., blue carbon, fishing and tourism), but is often omitted from future climate projections. Sediment transport is driven by hydrodynamics (e.g. tides, river runoff, waves and storms), sediment properties (e.g. cohesiveness and particle sizes, and composition), and their interactions with biology (e.g., extracellular polymeric substances and vegetation) (Solan et al., 2023). Most sediment models are sub-regional or local (e.g. Kondolf et al., 2018). Insufficient data of sediment distributions on the seabed and fluxes through open boundaries, as well as our limited knowledge of biophysical interactions between cohesive, non-cohesive sediments and biology, hampers their performance.

Sediment transport in the coastal ocean is also a key process in driving the nutrient, carbon and oxygen exchange between the ocean floor and water column (e.g. Moriarty et al., 2021). The resuspension of nutrient rich sediment can be a major source of plankton productivity and also impact light availability (e.g. Maggiorano et al., 2025). For example, a major impact of cyclones in shallow tropical regions, such as the Great Barrier Reef, starts with the blocking out of the water column light by wave resuspension of sediment, followed by an increase in plankton productivity (due to nutrients being released from the sediment) and settling of the organic matter, enhancing benthic productivity of fast growing species. This example shows a tight coupling between sediment transport, sediment biogeochemistry, benthic ecology and ocean circulation.

Estuaries and fjords

As semi-enclosed waters at the interface between sea, air and terrestrial fluxes, estuaries and fjords are highly dynamic coastal systems and vulnerable to the impacts of dynamic shifts and extreme events, and mediate the exchange of material (e.g., chemicals, microplastics, carbon, nutrients, sediment, salt, and freshwater) between land and sea. Estuarine dynamics are controlled by both terrestrial and marine processes spanning a wide range of spatial and temporal scales. To accurately predict and better understand the impact of climate change on these marine ecosystems requires models that fully resolve, and ideally dynamically couple, estuarine dynamics with shelf sea and terrestrial dynamics. For example, the coastal retention of nutrients in the Stockholm archipelago has been projected to increase in the future (Wåhlström et al., 2024), while is also influenced by input of nutrients from the Baltic Sea, which in turn is influenced by nutrient input from multiple rivers and coastal retention.

Future climate impacts on developed, interconnected floodplains are particularly critical in heavily populated and industrialised estuaries, where low-lying floodplains are widely used for critical infrastructure. Industrialised estuaries and deltas support transport and energy infrastructure, water supply and access (i.e. ports and harbours), and 21 of the world's 30 largest cities are located next to estuaries. It is of critical importance to fully capture and understand marine and fluvial drivers of flood hazard on the shores of estuaries for accurate climate hazard assessments (e.g. De Dominicis et al., 2020).

The impact of climate change on estuarine water quality is poised to disrupt various ecosystem functions and services. Alongside accelerating estuarine salt intrusion and turbidity, issues driven by intensified droughts and storms, and human activities have introduced significant concerns for estuarine water quality, notably due to excess nutrients, microbial contamination, and hazardous chemicals in many estuaries worldwide (Cloern et al., 2016). Estuarine water quality is controlled by multiple physical, biogeochemical, and ecological processes, including, for example, the detailed response of bacteria and viruses to environmental conditions. Human activities such as aquaculture, agriculture, sewage discharge and dredging further compound this complexity.

Estuarine climate impacts modelling present challenges in terms of spatiotemporal scales, requiring local or urban scale (O10 m) resolution and sub-daily-scale atmospheric, riverine and tidal forcing. Whereas, predicting morphological changes can require decadal simulation times. Extreme events impacting estuaries have been shown to be co-dependent, e.g., high surges and river flows following storm events (Bevacqua et al., 2021; Couasnon et al., 2020), and so require joint-probability analyses. Sitting between oceanographic and hydrological science disciplines, estuaries tend to 'fall between the cracks' and so are underrepresented areas with respect to current knowledge of climate change impacts at local scales. The vast range of differing conditions among estuaries impedes generalisation of theories and modelling and a lack of fine-scale monitoring often hinders model configuration (e.g. unknown estuarine depth), calibration and validation.

Addressing the need to comprehensively treat the impact of climate change in multiple estuaries requires a combination of modelling approaches from low complexity, e.g. 1D box models (Verri et al., 2020; Wåhlström et al., 2024) to high complexity, e.g. 3D unstructured mesh modelling of the river-sea continuum (e.g. De Dominicis et al., 2020), alongside various observational-data and model-data driven machine learning based approaches (e.g. Saccotelli et al., 2024). Modelling estuarine dynamics is also crucial to provide an accurate representation of riverine fluxes in global ocean models (e.g. Sun et al., 2017).

3.5. Polar coastal ocean modelling

The threat of climate change to polar coastal ocean regions and the local communities and ecosystems that depend on them is well established, e.g. through loss of summer and multiyear sea ice, and increased exposure to wind and waves with consequent enhanced erosion. Polar seas also play a significant role in the global climate system. Understanding climate change in the polar ocean, along with feedback from ocean-ice-atmosphere interactions, is crucial to understanding future climate scenarios. For example, sea ice plays a key role in determining surface heat fluxes, changes in nutrient supply and productivity in polar oceans, as well as interactions between the polar and sub polar waters. Moreover, the interaction between the coastal ocean and icesheets and glaciers in both northern and southern hemispheres is crucial for understanding the mass-addition component of sea level rise and how this might change into the future.

The Arctic Ocean has been modelled for several decades now, driven by major collaborative initiatives such as AOMIP (e.g. Popova et al., 2012) and FAMOS (Proshutinsky et al., 2016). Many of these efforts have focused on the open ocean and issues such as sea ice loss, storage of freshwater in the Beaufort Gyre and the 'Atlantification' of the Arctic Ocean through enhanced Atlantic water penetration. These efforts have led to several inter-comparison projects, which reported on the state of the art of this modelling at the time (Ilıcak et al., 2016; Wang et al., 2016a; Wang et al., 2016b). Recent work has included models reaching 1 km resolution to consider the role of eddies and other mesoscale processes (Wang et al., 2020).

However, there has been much less modelling of the coastal regions and shelves. This is unfortunate given that it is in these regions where communities interact with the sea, and where river water (freshwater, nutrients and carbon) enters the Arctic Ocean. In a series of papers, Carmack et al. (2015) introduced the concept of the Arctic shelves as a contiguous pan-Arctic riverine domain, with processes depending on whether a given shelf is interior or linked to an Arctic gateway. Modelling of Siberian shelves such as Laptev and Kara seas has focused on freshwater, sea-ice and ecosystem processes (e.g. Wassmann et al., 2015), while modelling studies of the Chukchi and Alaskan coastal shelves have explored routes for Pacific Water, inflowing through Bering Strait, to reach the Arctic Ocean interior. Modelling of the Canadian Arctic Archipelago, which is effectively one shallow shelf, initially focused on understanding what drives the exchange between the Arctic Ocean and the Atlantic, including through Baffin Bay. Recent studies are now looking at more regional scales, relevant to communities and especially considering ecosystem processes (Bhatia et al., 2021). Some initial ocean-climate downscaling studies have been carried out (e.g. Buchart et al., 2022) to look at the evolution out to 2070 of the North Water Polynya, a biologically important region. A recent major project has developed modelling tools (Myers et al., 2024), and is using downscaled CMIP model output (Braun et al., 2021) coupled with hydrological modelling to examine processes in the Hudson Bay Complex, and explore the relative role of climate change and river regulation on the bay system (Lukovich et al., 2021). An important topic to progress is finding ways to integrate and co-produce knowledge with local indigenous communities (e.g. Bishop et al., 2022).

3.6. Alternative modelling approaches

Data-driven approaches provide an alternative to dynamical downscaling. While these have not yet been widely used for future climate projections in the coastal ocean, they offer an important emerging capability with the potential to overcome many of the issues associated with dynamical approaches. Data-driven models generally involve models based on empirical relations described by statistical and/or machine learning approaches (e.g. artificial neural networks) to link larger scale drivers with the local and regional response to climate change, in contrast to dynamical models based on numerical solutions of differential equations. The training data can involve observational time-series and/or reanalyses, but for the climate change context it needs to cover multidecadal timescales. Data-driven approaches are highly computationally efficient allowing a much wider range of simulations than dynamical models. For example, van Hooidonk et al (2016) statistically downscale SST from CMIP5 ESMs to all coral reef systems globally based on NOAA Pathfinder v5.0. Data-driven approaches are generally steady state and often lack constraints of underlying physical principles (e.g. equations of motion and conservation laws), although *Differentiable Machine Learning* (Shen et al., 2023) aims to close these gaps. Their ability to help identify underlying physical mechanisms relies on the approaches of *Interpretable Machine Learning* (Jiang et al., 2024), either through inherent interpretability of the data-driven model (multiple linear regression being a very simple example) or through various analysis tools to extract relationships *a posteriori* from the 'black box' machine learning model. However, whether a significant relationship between the large-scale climate and local data exists is highly location and application dependent, e.g. it may be absent due to strong internal dynamics. Moreover, changes beyond historically observed bounds or involving qualitative shifts are difficult to capture. Hence, while a single regional dynamical model can be applied universally to different regions with only minor modifications, data-driven models generally need to be trained to locally specific conditions. A potential application of the classification approaches discussed above relates to machine learning based model training. If two regions are identified as having similar dynamical characteristics, an open question is whether a machine learning model trained on one region can be effectively used in another?

Hybrid dynamical-data-driven modelling methods aim to address these short comings while preserving the computational efficiency of purely data-driven approaches. Emulators or surrogate models typically operate by simulating a representative subset of scenarios using a numerical model. These simulations are used to calibrate a statistical model or train a machine learning algorithm, and the prediction ensemble can then be expanded beyond the initial dynamical model realisations. Hybrid dynamical-data-driven methods have been used to downscale present-day wave conditions (Camus et al., 2011; Ricondo et al., 2023), to investigate waves induced by tropical cyclones (van Vloten et al., 2022) and conduct future climate projections of surface waves coupled with storm surges (Anderson et al., 2021). Hermann et al (2019) use a statistical approach to expand their ensemble of dynamically downscaled simulations of biophysical conditions in the Bering sea. Another category of hybrid methods, known as additive models, are based on classical Green's functions and enable the segmentation of surface wave downscaling process into several subprocesses (Cagigal et al., 2024). Consequently, the reconstruction of an event involves the linear combination of responses from individual subprocesses, thereby eliminating the necessity of selecting a limited number of cases and broadening the applicability of the method to future wave climates and conditions never historically observed.

A new class of models is emerging that directly combines dynamical, machine learning and/or theoretical approaches. A coarse scale dynamical model provides large scale constraints and a machine learning model (Kochkov et al., 2024; Zanna and Bolton, 2020) or dynamical systems theory (Shevchenko and Berloff, 2023) provide fine scale detail; essentially a coarse resolution model is developed to behave like a fine resolution one, with a substantial reduction in computational cost. While not explored in the coastal ocean yet, such approaches are conceptually highly attractive for the challenges of local scale climate downscaling.

In addition to data-driven approaches, simplified (semi-) analytical models (i.e. theory-driven approaches) are valuable tools for comprehending uncertainties related to the impacts of natural and human-induced changes (Schuttelaars et al., 2013; Wei et al., 2022), as well as uncertain climate projections. These models are highly cost-effective and can effectively isolate the contributions of various processes. As a result, they can be employed to gain insight into the complex spatio-temporal variabilities in model variables, identify the reasons behind any disparities between simulated and observed data, and explore the sensitivities of biophysical variables to different environmental conditions and system settings (e.g. by running thousands of simulations). This capacity can be extremely beneficial in identifying parameter spaces that could lead to potential regime shifts in future climates and understanding the consequences of different future projections and human mitigation measures for marine environments and coastal communities.

4. Uncertainty and simulation strategy

4.1. Uncertainty

In climate impacts studies model experiment design and uncertainty are intrinsically linked; there is no 'right' answer in future climate projections. Hawkins and Sutton (2009) provide an important framework for the analysis of uncertainty, dividing it between scenario uncertainty, model uncertainty, and natural variability. In this context, the first two relate to the choice of driving ESM experiments: the range of emissions scenarios and the choice of ESM run under that scenario. In downscaling studies, there are extra layers of model uncertainty arising from the downscaling model choices: its structural and parameter uncertainty, and the specifics of how the ESM forcing is implemented (including atmospheric downscaling, land surface processes and bias correction). A single pathway into the future can be very useful in exploring the system's response to forcing, often outside of the current observational base. Compounding uncertainties from multiple sources, and the comparative shortness of the observational record (on climatic timescales) have led to the emergence of non-probabilistic approaches that develop "storylines": physically self-consistent and plausible future events or pathways (Palmer et al., 2024; Shepherd et al., 2018). However, even a semi-quantitative estimate of the likelihood of such futures is immensely useful for guiding policy response options. Ensembles of simulations are then the primary method of capturing uncertainty in this context. While generating large ensembles can be prohibitively expensive, it is possible to use statistical models or machine learning emulators trained on a comparatively small ensemble, to help span the uncertainty space within the ensemble (e.g. Hermann et al., 2019). The different uncertainty elements can provide an uncertainty budget for the marine projections, and it is possible to bring them together into a single uncertainty estimate.

Scenario uncertainty

Scenario uncertainty, from a marine downscaling perspective, is dictated by the Representative Concentration Pathway (RCP) and the Shared Socio-economic Pathway (SSP) used to drive the forcing ESM, established by the CMIP protocol. There are no explicit likelihoods associated with these scenarios, and the impact of human activities and policies made to reduce emissions may not be evident for several years through technology and economic inertia to policy. Moreover, there are many potential human changes, not related to greenhouse gas emissions, that may have as big an effect as climate change, particularly in the near coastal zone, e.g. land-use changes, demographic shifts and urbanisation. Among the most severe disturbances in the coastal ocean are impacts due to fisheries, aquaculture, renewable energy production, sediment dredging, mining and dumping, and, potentially in the future, mCDR activities. These can be incorporated into the scenarios, but often require additional modelling activities, such as land surface modelling (e.g. Beusen et al., 2022) and add significant levels of modelling uncertainty. The choice of emissions scenario depends on the application: first order investigations of climate response often consider a high emissions scenario, e.g. RCP8.5; although the likelihood of this future scenario is contested (e.g. Hausfather and Peters, 2020; Schwalm et al., 2020). Adding a mitigation scenario provides additional information on avoided damage, i.e. it quantifies the benefit, in the marine context, of a particular emissions reduction pathway. The timescales of the simulations are also an important consideration as many SSP scenarios (and the climate system response to these) only diverge later in the century and so mid-century simulations may see little benefit from more than two scenarios.

Climate model uncertainty

Regarding ESM forcing, two main types of ensembles can be employed: an *ad hoc* ensemble of opportunity or a systematically designed approach. The first uses existing ESM simulations, e.g. from CMIP, to build an ensemble. This approach is comparatively straightforward to implement but does not necessarily span the full range of uncertainty. The CMIP Multi-Model Ensemble (MME) is made up of simulations from different modelling centres and is confounded by each modelling centre developing the "best" model they can, according to their own criteria, rather than attempting to span the uncertainty across the ensemble. Hence, the MME is likely to under-sample the full range of model structural uncertainty. Systematically designed ensembles require a type of uncertainty to be selected, and model simulations tailored to span the range of the uncertainty associated with it. For example, the UKCP18 Perturbed Parameter Ensemble (Sexton et al., 2021) spans the range of uncertainty associated with 25 members based on the choice of atmospheric parameters within a single ESM (HADGEM3), and a selection of these are used to explore uncertainty in a downscaled regional ocean model (Tinker et al., 2024).

Addressing which ESM to include in a multi-model downscaling framework remains an active research area. A common approach is to select those ESMs that perform better during the historical period in the target region (e.g. Hermann et al., 2019). However, models that best match the observed historical climate are not necessarily ones that will most accurately represent future climate sensitivity. A potential avenue is to use process-based model selection methods, e.g., with emerging constraints (Eyring et al., 2019; Hall et al., 2019). Other approaches include selecting the ESMs that capture the range of projected future mean changes of key oceanic (physical and/or biogeochemical) properties (e.g. Pozo Buil et al., 2021), prioritizing ESM spread over scenario uncertainty. The CORDEX project provides the opportunity to explore the uncertainty associated with downscaled atmospheric forcing.

All the model choices related to coastal ocean downscaling discussed above add a layer of uncertainty related to the future projections (if a different choice were made, the projections would give a different answer). While there is sometimes scope to explore the parameter and internal model choices (e.g. mixing schemes), exploring model resolution and/or coastal ocean model selection (e.g. ROMS versus NEMO versus MOM6) is often beyond the scope of a single downscaling study. Hence this uncertainty is often neglected and is an aspect that GCO-MIP Strands 3 aims to make progress with.

Propagation of uncertainties also occurs "downstream" of linked models. For example, in an end-to-end modelling framework to produce future regional projections of Pacific sardine using three different ecological models forced by three downscaled climate projections for the California Current, Smith et al (2023) found that the relative contribution of uncertainty associated with ecological model type increased as the projection period increased, while the relative ESM uncertainty decreased. On the other hand, Hinson et al (2023) used ESMs to force regional watershed models and found that the majority of the total uncertainty in watershed runoff and the greatest fraction of total uncertainty for future hypoxia levels in the Chesapeake Bay resulted from ESM selection. Hence, attempting to account for every source of uncertainty, is not only exceptionally challenging, but also increases the potential to overestimate joint uncertainty, mask or obscure important signals, and hinder the ability to provide climate and management advice. A potential solution is "to identify the most important sources of uncertainty that propagate through the regional projections and ensure the interpretation of results acknowledges the variation and uncertainty that remains unmodeled" (Smith et al., 2023).

Natural variability

Because ESMs are run for many 100 s years unconstrained by observations, the simulated phase of natural climate variability (e.g. ENSO, NAO, PDO, etc.) is essentially random, and bears no relation to that in the real world. This is in contrast to historical re-analyses in which this phase is constrained by data assimilation, and to seasonal and decadal forecast systems that initialize a forecast from a data assimilating simulation. The natural variability provides a lower limit on the averaging period needed to separate a significant climate change signal. The World Meteorological Organisation prescribes a canonical averaging period of 30 years, and so comparisons of averages shorter than this are likely to be contaminated with differences in phase of natural variability. Hawkins and Sutton (2009) show this aspect of uncertainty is highly regionally variable and its relative importance decreases with projection lead time; natural variability uncertainty remains largely constant while scenario uncertainty grows. Ensembles can ameliorate natural variability uncertainty, allowing shorter periods to be considered. These can either be multi-model ensembles, which then mix the natural variability and model uncertainty, or initial condition ensembles, which provide a 'clean' assessment of natural variability, and form the basis for decadal climate projections.

How these modes of natural climate variability translate into the regional downscaled simulation remains an area of active research. For example, Pozo Buil et al. (2021) showed that the regional response of upwelling-favourable wind stress in dynamical downscaled projections is correlated with basin-scale climate oscillations (the PDO).

4.2. Simulation strategy

Forcing and bias correction

Full physics coastal ocean simulations require forcing from atmospheric, oceanic and terrestrial variables and/or fluxes. Atmospheric forcing can be taken directly from ESMs (Fig. 4c), utilise downscaled regional atmosphere models (such as from CORDEX; Fig. 4e), or are included in the coupled configuration (Fig. 4g). Ocean forcing can also be taken from the ESM or alternatively from a global forced ocean model (Fig. 4d) or larger area (e.g. ocean basin scale) forced or coupled model. The general principle is to initialise the coastal ocean model with the same data as the oceanic boundary conditions, to prevent spurious baroclinic boundary currents that can persist throughout the whole simulation; geostrophy preventing an interior adjustment to the boundary conditions.

Terrestrial forcing (from rivers and land-ice melt, including water, heat carbon and nutrients) is a particular challenge for coastal ocean downscaling. The information can be taken from the ESM land surface component with an additional treatment for ice sheets if required (not commonly included in ESMs), by perturbing present-day river discharge observations with climate information (e.g. catchment precipitation), or from the output of a hydrological model forced by consistent atmospheric information (Saraiva et al., 2019b; Stadnyk et al., 2021). There is generally a considerable mismatch in spatial scales between the land surface component of ESMs and coastal ocean models (particularly at sub-regional and local scales), so some form of terrestrial downscaling is usually required to accurately model the riverine input.

Errors in large scale (atmospheric and oceanic) forcing tend to propagate into the regional model. Although, from the ocean side, this can be ameliorated to some extent by choosing a sufficiently large area so internal dynamics can compensate for errors at the boundaries. The forcing datasets for the downscaling ensemble can be selected based on the realism of the large-scale patterns during the historical period (important to prevent error-propagation), and the divergence of their response to climate change, so key elements of uncertainty and bounds of likely response are captured. When error propagation is expected (or tested) to excessively degrade the simulation and counter the benefits of downscaling, a pre-processing stage is required to correct these biases. ESM biases in mean state and/or variability are quantified over a historical reference period and removed from the forcing used for downscaling. Many ESM bias correction methods have been developed (e.g. Pozo Buil et al., 2023; Xu et al., 2021), mainly focused on climate and atmospheric applications. For coastal ocean applications, there is no consensus on whether to use bias correction and which method is best (Drenkard et al., 2021). However, studies without any bias correction can lead to extremely large biases at local and regional scales (e.g. Holt et al., 2022); and bias correction has been demonstrated to reduce this in both hydroclimate (Rahimi et al., 2024) and ocean (Pozo Buil et al., 2023) variables. For downscaled ocean projections, the "delta method", usually following the time slice simulation strategy (see below) is most common. In its simplest form, the time-mean differences (deltas) in the ESMs between historical and future periods are derived and added to reanalysis based on historical conditions. In the "seasonally-varying" delta approach (Alexander et al., 2020) the seasonal cycle of the long-term deltas is retained and added to the control simulation forcing. In the "time-varying" delta method (Pozo Buil et al., 2021), the deltas are first computed from a period of interest relative to a historical period and then added to a historical climatology and high-frequency variability (Echevin et al., 2020; Pozo Buil et al., 2021). It is important to apply consistent bias correction approaches to both atmospheric and ocean forcing, and also to the initial conditions.

A particular issue for regional models with a biogeochemical component is the need to provide accurate boundary conditions for these state variables that include their wider climate change signal. This often limits the choice of forcing to coarser resolution ESMs, which have a marine biogeochemical component and even then, approaches for specifying missing variables are often needed (e.g. through Redfield ratios). This potentially restricts the choice of ensemble members and the ability to span uncertainty in this context. Temporal resolution of depth resolved data is a particular issue, with at least monthly forcing being required. While data availability has significantly increased in CMIP6 compared to CMIP5, biases in this data remain an issue. Climatological values for the main biogeochemical boundary conditions (e.g. from WOA or GLODAP) perturbed by a climate change single is a viable solution (essentially a bias correction approach), e.g. Siedlecki et al (2021). However, care is needed to maintain consistency with the climate change signal in the hydrography. This highlights the utility of the forced global approach (Fig. 4d) for providing consistent biogeochemical boundary conditions for finer scale models (e.g. Wakelin et al., 2020).

In contrast, reduced complexity models require correspondingly simpler forcing, although may come with other requirements, e.g. a 2D storm surge model might only need wind and pressure atmospheric forcing but requires these at high frequency and is highly dependent on the forcing model's ability to simulate atmospheric extremes.

Transient simulations

In the transient simulation approach models run continuously, starting from the recent past and proceed into the future with time varying forcing. This is the typical approach used for scenario simulations in CMIP, in which, following a long pre-industrial spin-up, the ESM runs for the historical period followed by a future scenario (e.g. 1850–2100). A shorter period is usually used for downscaling; for example Echevin et al (2020) run 1997–2100 with 1997–2005 treated as spin-up. In this approach, the transient impacts of climate change can be determined for plausible future conditions and warming targets without requiring a predefined plan for the time horizon that these conditions and warming targets will be reached. Most importantly, the transient approach generally ensures that the regional model has sufficient time to adjust to the forcing (although see comments on spin-up below), and the simulations explicitly include the regional model's natural long-term variability. Hence, the climate change induced trends can be inferred without contamination from natural variability (Drenkard et al., 2021). Transient simulations of sufficient duration enable the isolating climate change signals from natural variability and are particularly crucial for detecting and attributing signals in the coastal ocean.

Some period of spin-up needs to be accounted for as the model adjusts from its initial conditions and reaches a dynamic equilibrium with its forcing. In most regional seas this is comparatively fast (less than a few years); the oceanic flushing time of the region is a good guide. However, care is needed in deep basins where the deep-water exchange time can be very long, such as the Black Sea (~400 years; Murray et al., 1991) and Baltic Sea (~30 years), or for biogeochemical tracers that require similarly long equilibration time (e.g. semi-refractory DOC or benthic pools). In these cases, as with the deep ocean in general, a disequilibrium between the forcing and the internal model state can lead to an erroneous trend signal or 'drift'. This can be established using a control run, e.g. one with repeating climatological mean seasonal forcing for the historical period. It is common practice to subtract any resulting drift from the climate change signal. For example, Wakelin et al. (2020) assess drift in their downscaling simulation of the NW European shelf over a 120 year period and show it to be negligible for SST, surface salinity, and near bed oxygen in most regions of the model.

Generally, the transient approach is considered best practice for future climate downscaling. However, in high-resolution (sub-regional and local scale) and/or O-A coupled simulations other approaches that reduce the computational cost are required.

Time-slice simulations

The time-slices approach typically involves a pair of relatively short (10–30 years) model experiments driven by (i) present-day conditions (e.g., 1996–2015) and (ii) future conditions (e.g., 2081–2100), each prescribed from the same ESM simulation. The climate change signal is then estimated by comparing mean properties of these two experiments. This approach is computationally more efficient than the transient approach and has been used effectively in many studies (e.g. Holt et al., 2016; Nishikawa et al., 2021; Oerder et al., 2015). However, spin-up adjustment from initial conditions (noted above) and natural variability contamination can lead to uncertainty in the interpretation of the resulting climate change signal. Longer time-slices or use of an ensemble can reduce the issue related to the attribution of natural versus climate change induced variability (Drenkard et al., 2021). However, the benefits over a transient simulation become marginal for longer time-slices. Time-slices are often the only option for kilometre or sub-kilometre scale simulations. In the case of shallow coastal seas initial condition adjustment is very fast, and less of an issue. However natural variability contamination remains an issue for short time-slices. Approaches need to be developed to ameliorate this, for example by selecting two short time-slice periods with matching phase of the natural variability in the forcing data. Alternatively, they can be selected by choosing time-slices whose mean forcing matches the longer-term mean, for example when the 5-year mean is closest to the 30-year mean. For example, in their 700 m resolution simulation of Puget Sound, Moore et al (2015) select individual years to simulate "whose seasonal cycle of wind stress were closest to decadal means for the 1980 s and the 2040 s (1988 and 2047)". For multiple forcing variables, a cost-function minimisation can be applied to select sorter time slices.

Climate delta simulations

In the climate delta (or pseudo-Global Warming) approach, a control run is forced with reanalysis products (e.g. for 30-years of the recent past) while future scenario runs add a climate change signal to the forcing of the control run (e.g. Alexander et al., 2020; Jin et al., 2021), using either an additive or fractional-change approach. This readily incorporates a bias correction and provides a further reduction in computational cost over the time-slice approach if a reanalysis forced simulation is already part of the simulation strategy (e.g. for validation, see below). It is challenging, however, to maintain dynamical consistency in the forcing data (e.g. changes in wind direction), and as with the time-slice approach, it is difficult to explore changes in higher frequency variability, e.g. storm tracks and climatic modes, and questions of initial condition adjustment persist.

4.3. Building confidence in future projections

Trust in future climate projections is built on a combination of a regional model's ability to reproduce present day conditions (including trends and variability), and confidence in the model formulation itself; that it is based on sound theoretical and/or empirical understanding (e.g. governing equations and conservation principles). It is particularly important that the model formulation is robust to environmental changes that go beyond those experienced through historical natural variability, e.g. encompassing state-changes and regime shifts.

In ESMs, climate variability has essentially random phase and this must be accounted for in any comparison with observations. Comparisons can be made to hindcasts, reanalyses and observational climatologies averaged over long periods (e.g. 30 years) to average out climate variability. Probability distributions and trend metrics can be used to assess the statistics of model performance; these need to be calculated over decadal time scales to control for climatic variability.

There is great variation in the availability of data for model assessment in the coastal ocean, largely following gradients in wealth but also challenges in regional accessibility (notably in high-latitude, ice-covered seas). While some regions benefit from extensive sustained coastal ocean observing, the coastal ocean lacks the systematic international observing networks available in the open ocean, such as ARGO and GO-SHIP. Specific care is needed with gridded observational products, since these can mislead by providing 'observed' values where there is insufficient data to make a sensible interpolation. This requires careful use of product *meta*-data or else resorting to raw observations for the assessment (the safest approach). Closing these observational gaps through high resolution satellite earth observation and novel low-cost sensors (e.g. GNSS sea level monitoring) is critical for global coastal ocean climate projections. Comparability of models between regions also helps: validation of a model configuration in a data rich area lends some confidence to performance in a data poor one, as long as they share common dynamics, a key motivation for typology approach (Section 2.2).

A standard set of model assessment diagnostics is a key component for a model intercomparison programme, e.g. ESMvaltool.org for ESMs and COAsT for regional models; (Byrne et al., 2023). In the global coastal ocean, some variables are more discerning than others in assessing the skill of a simulation, but a standard set of diagnostics needs to be pragmatic in terms of data availability. For example, sea surface temperature (SST) is fundamental to several physical and biogeochemical processes and can be remotely sensed. However, in forced ocean simulations, SST is highly constrained and so its utility in assessing model accuracy is less valuable. In contrast, sea surface salinity is more strongly controlled by model dynamics in both forced and coupled simulations, and so is a better guide to model performance. Although it has fewer and lower resolution observations.

A key approach to evaluate regional downscaled climate models is to consider current trends and the processes responsible for these. For example, in the Northwest Atlantic (NWA), Ross et al. (2023) evaluate a regional MOM6 configuration against both climatologies and trends in SST and water masses. The NWA shelf is well known for experiencing rapid warming (Pershing et al., 2018), and the regional amplification of SST is thought to be driven by the increased presence of Gulf Stream water on the shelf, and so a comparison of the position of the Gulf Stream and on-shelf water masses provides a process-based evaluation. This builds confidence that the model can simulate future interactions with the Gulf Stream.

Coastal ocean processes, such as tides and benthic characteristics require bespoke validation approaches. Adding a reanalysis forced simulation to the strategy allows the model to be compared directly with contemporary observations, including the detailed high spatiotemporal resolution needed in the coastal ocean (e.g. for sea level extreme events). This can build on the extensive regional model validation developed for operational oceanography (Alvarez Fanjul et al., 2022; Sotillo et al., in review, 2024) and adds confidence in the model configurations that are then adapted for regional projections. Reanalysis forced simulations can also identify the implications of changing from reanalysis to ESM forcing on model skill; the expectation is some degradation in skill even for a statistical comparison, due to lack of observational constraints in the ESM (e.g. Holt et al., 2022).

There is an open question of how to build confidence in data-driven models (e.g. machine learning approaches). In the observation driven approach, excluding a subset of observations from the training set and using these for validation is common, but only an option when the training set is extensive. For model-based approaches, training with reanalysis and repeating the validation as used for the dynamic model is an option. In both cases, great care is needed in cases where the future climate goes beyond the observational base.

5. Actionable knowledge, data and capacity development

5.1. Sharing models

Sharing model code, configurations, and experiments, and the methodology to create these is a key part of reproducible[2] model systems. This is not only at the heart of the scientific method but also important in developing global capacity in coastal ocean downscaling. The practical realisation of a coastal ocean model simulation for future climate is a complex combination of:

- Numerical ocean model code, configuration and forcing
- Practitioner expertise across the model components
- The High Performance Computer (HPC) infrastructure
- A third-party software stack for successful compilation and execution on the HPC
- Workflows and scripts to complete these stages

Documenting these processes to allow for reproducibility is challenging but is a key step for both cross-model comparison and globally expanding the climate downscaling community. Model descriptions in journal papers provide the traditional method of sharing. Unless done with great care, they rarely provide a reproducible solution. An overview of the fundamentals of building reproducible and relocatable regional ocean models is given by Polton et al. (2023). The use of code collaboration platforms (e.g. GitHub) and the ability to publish model configurations from these with a DOI (e.g. on Zenodo) provides the beginnings of a genuinely reproducible solution. An example is the Salish Sea MEOPAR Project (https://salishsea-meopar-docs.readthedocs.io/en/latest/code-notes/salishsea-nemo/index.html). This includes extensive documentation for a regionally specific NEMO configuration of the Canadian Salish Sea, which is deployed in various research projects (e.g. Soontiens and Allen, 2017). Similarly, the Canadian NEMO Ocean Modelling Forum Community of Practice (https://canadian-nemo-ocean-modelling-forum-commuity-of-practice.readthedocs.io/en/latest/) describes regional configurations and experiments, and developments of such in Canada.

Relocatable modelling systems provide an important tool for expanding the coverage of future climate downscaling. Often developed with operational forecasting or short-term process studies in mind, they are readily adapted to future climate applications to provide easily deployable end-to-end modelling solutions. For example, the NEMO nowcast framework (https://nemo-nowcast.readthedocs.io/en/latest/) is a well-documented collection of Python modules that can be used to build a software system to run the NEMO ocean model in a daily nowcast/forecast mode. The Structured and Unstructured grid Relocatable ocean platform for Forecasting (SURF: https://www.surf-platform.org/tutorial.php; Trotta et al., 2021) uses both NEMO and the SHYFEM unstructured grid model to rapidly build and deploy configurations for real time maritime disaster response. The focus is on operational deployment and reliability, and this necessitates a high level of automation and reliance on mature code versions.

Containerization is an emerging technology in the field of ocean modelling and potentially offers promising opportunities for sharing models and porting to new architectures, by abstracting the challenges of compatibility between operating systems and library dependencies from running the models. Essentially, it allows a fully working realisation of the model system to be shared, and this can be deployed on any computer resource that supports the chosen containerization system; Singularity (https://sylabs.io) is a notable example designed for HPC systems, and so well suited to this task. Containerization is less likely to be adopted by centres working on a single HPC platform, as there is an efficiency cost associated with the container layer, but is well suited for institutions and practitioners that rent cloud-based HPC resources or use multiple community facilities.

5.2. Sharing data

Data access is an on-going challenge in downscaled future climate projections; they are very storage intensive, due to the need to explore high frequency processes at decadal to centennial scales. Regional modelling communities lack the internationally organized data storage and distribution infrastructure available to the climate modelling community (e.g. the Earth System Grid Federation; ESGF). Careful consideration is required as to which parameters to store, at what temporal and spatial resolution, and the use of standard sets of bespoke metrics/diagnostics, which can be calculated on-line to reduce storage cost. These go beyond the standard set of essential ocean and essential climate variables. End users have different demands on the downscaled climate data provided. Some need raw model data to analyse and interpret independently, others require a synthesised products that provides information on specific questions. This requires various, web-based, data access approaches, as well as end user interaction to produce bespoke products such as maps and diagrams. All this requires a high degree of organisation and coordination before simulations are started (GCO-MIP Strand 4). This can be aided by standardisation of formats (e.g. netCDF4, ZARR), vocabularies (e.g. CF Standard Names) and data access approaches (e.g. ESGF nodes or cloud-based infrastructure). In addition, standardisation also promotes confidence and trust in the data. The collective data-basing of downscaled climate data facilitates cooperation between neighbouring countries and regions. CoastPredict and the UN Decade Collaborative Centre for Coastal Resilience aspires to develop a cloud-based infrastructure framework to support data management and digital services across the global coastal ocean. This builds on a vision of Regional Clouds supporting multiple GlobalCoast pilots sites (Section 2, Fig. 3) and provides a solution for disturbing coastal ocean projection data (e.g. from GCO-MIP) under FAIR data principles.

5.3. Translating model results to usable solutions

The end users for climate downscaling information in the coastal ocean span the breadth of the marine economy, environmental protection and management, and coastal resilience sectors, both directly and via *intermediate users* across a diverse range of disciplines. Each end user community has their own set of perceptions, beliefs and values, which can act as a barrier and/or opportunity to the provision of the

[2] Here "reproducibility" is taken to accept differences in computational environment, which can lead to scientifically different results particularly in areas where stochastic processes (e.g. eddies) are important, but are often insignificant compared with other uncertainties.

projections. These diverse end users act in international (global and regional), national and local contexts, spanning public, private and "third sector" (e.g. NGO's) organisations. Engagement via coordination frameworks is highly beneficial when a broad level of end-user engagement is desired. Examples include, UN Decade programmes, WCRP activities and regional cooperation bodies, e.g. Partnership for the East Asian Seas (https://www.pemsea.org/).

A balanced view and clear explanation of uncertainty is crucial for end-user engagement. For example, being clear on the distinction between lack of knowledge of the system's response to climate change and large uncertainty in that response; we may know the process response of the system very well, but still have a broad range of possible futures, e.g. due to chaotic interactions. Moreover, understanding the endusers' objectives is critical, e.g. do they need to design to a worst-case scenario or a most likely scenario? Typically, this balances the cost of overestimating the hazard against the risk of underestimating it.

The results from downscaling simulations need to be co-designed and co-produced into usable solutions with the end users, in the form of readily accessible data, information and advice. This delivers GCO-MIP Strand 4. This increasingly includes opportunities for end users themselves to participate in the research so that outputs are useful, useable, and trusted, with the help of coordinated frameworks and boundary spanning institutions. Given the complexity of delivering usable solutions across this diverse end-user community, it is helpful to identify a community of practice sitting between the downscaling practitioners and the ultimate end-users of the information, termed *intermediate users* in the Copernicus Marine Service (Le Traon et al., 2019). These develop bespoke information products and services for specific end-users and also feedback design requirements to the downscaling practitioners. In this context, local knowledge is extremely valuable in designing experiments, understanding results and building confidence in modelling results, but noting the epistemology (or "ways of knowing") underlying this maybe unfamiliar to the modelling practitioners. Moreover, the natural science information provided by these projections needs to be combined with social, cultural and economic indicators to develop detailed environmental exposure and vulnerability assessments and so inform effective coastal ocean resilience strategies. This co-design often requires transdisciplinary collaborations, i.e. collaborations that reach across scientific disciplines (e.g., environmental sciences, engineering, economics and social sciences) and sectors (e.g., academia, industry, NGO's and policy). A significant challenge of such work is effective communication between disciplines and sectors, and in particular communicating how we account for new scientific evidence, while minimising any loss of confidence due to a perception of "moving the goal posts". Particularly, new scientific insights often increase, rather than reduce, uncertainty, as new process responses are identified. Moreover, developing projections for multiple, diverse end users may lead to conflicting priorities, complicating the co-design ideal.

6. A proposed framework for a Global Coastal Ocean Model Intercomparison Programme

The great diversity of challenges and approaches outlined here, alongside the disparity of resources available to meet these across the global coastal ocean, implies that a coordinated coastal ocean model intercomparison programme requires a highly flexible and inclusive approach. Tables 1 and 2 summarise our analysis of the state-of-the-art for coastal ocean downscaling simulations targeted at ecosystem services and coastal hazards respectively (see Section 1.1). This forms the basis of the simulation strategy and protocols. Simulations targeted at aspects of the blue economy would be covered by one of these schemes, maybe with the addition of sector-specific parameterisations or models (not prescribed here). We propose a tiered approach to allow the widest participation in GCO-MIP. This approach consists of four inter-related strands, which can be participated in together or independently. Organising and facilitating the GCO-MIP itself requires some resource,

Table 1
Options for experiment design in GCO-MIP, for simulations targeting ecosystem services (see Section 1.1). *Optimal* options identify the current state-of-the-art, *Acceptable* are solutions matching earlier studies and *Advanced* is pushing the boundaries of current capability. These choices are only indicative and a real-world solution might cross these boundaries in some aspects, e.g. an *Acceptable* simulation run with more than one ESM forcing. Sim refers to simulations approach: T is transient simulations (Section 4.2); TS are time slice or climate-delta simulations (Section 4.2). Hydo: hydrodynamic model; BGC: biogeochemistry/lower tropic level ecosystem model; Waves: spectral wave model; Hydrol: hydrological model. Applications indicate example uses of these simulations, noting more advanced models usually cover those of less advanced ones. SLR: sea level rise; LMR: living marine resources; LBC lateral boundary conditions of nested models. HTL: Higher Trophic Levels.

Targeting Ecosystem Services								
Regional	Model	Scale (km)	Atmos Forcing	Ocean Forcing	Land Forcing	Sim	Ensemble	Application
Acceptable Fig. 4c	3D-hydro	5–12	ESM	ESM	Perturbed climatology	T	1 ESM 1 SSP	Circulation, Hydrography, Connectivity, Inferred ecosystem, SLR
Optimal Fig. 4f	3D-hydro-BGC	3–7	Downscaled	Global forced	Hydrol-land Model	T	2 ESM 2 SSP	BGC multi-stressors, Multiple storylines, Link to LMRs
Advanced Fig. 4g	RCM-BGC	3–7	O-A coupled	Global forced	Hydro-land Model	T	2 + ESM 3 + SSP	Dynamically consistent response, Uncertainty budget
Advanced Fig. 4b	Global forced-BGC	10–25	ESM	–	Perturbed climatology/ESM	T	2 ESM 2 SSP	Global view of coastal ocean and feedbacks, Accurate LBCs
Also Consider	HTL modelling. Wave effects							
Sub-Regional	**Model**	**Scale (km)**	**Atmos Forcing**	**Ocean Forcing**	**Land Forcing**	**Sim**	**Ensemble**	**Application**
Acceptable	3D-hydro	1–10	ESM	Regional/Global forced	Perturbed climatology	TS	1 ESM 1 SSP	Fine scale circulation, Hydrography, Connectivity, Inferred ecosystem
Optimal	3D-hydro-BGC	1–5	Downscaled	Regional	Hydrol-land Model	T	2 ESM 2 SSP	Fine scale BGC multi-stressors, Multiple storylines, Link to LMRs
Advanced	RCM-BGC	1–5	O-A coupled	Regional	Hydrol-Land Model	T	2 + ESM 3 + SSP	Dynamically consistent response, Uncertainty budget
Also consider	HTL modelling							

Table 2
Options for experiment design in GCO-MIP, for simulations targeting coastal hazards. *Optimal* options identify the current state-of-the-art, *Acceptable* are solutions matching earlier studies and *Advanced* is pushing the boundaries of current capability. These choices are only indicative and a real-world solution might cross these boundaries in some aspects. Sim refers to simulations period: T is transient simulations (Section 4.2); TS are time slice or climate-delta simulations (Section 4.2).

Targeting Coastal Hazards								
Regional	Model	Scale (km)	Atmos Forcing	Ocean Forcing	Land Forcing	Sim	Ensemble	Application
Acceptable Fig. 4e	2D-hydro	5–12	Downscale	ESM	–	T	1 ESM 1 SSP	Storm surge, SLR
Optimal Fig. 4e	3D-hydro-Waves	3–7	Downscale	ESM	–	T	2 ESM 2 SSP	SLR, Extreme waves, Multiple storylines
Advanced Fig. 4g	RCM-Waves	3–7	O-A coupled	Global forced	Hydrol	T	2 + ESM 3 + SSP	Dynamically consistent response, Uncertainty budget
Advanced Fig. 4b	Global forced-Waves	10–25	ESM	–	–	T	2 ESM 2 SSP	Global view of coastal ocean and feedbacks, Accurate LBCs
Also Consider	Erosion modelling. Interactive wave coupling							
Sub-Regional	**Model**	**Scale (km)**	**Atmos Forcing**	**Ocean Forcing**	**Land Forcing**	**Sim**	**Ensemble**	**Application**
Acceptable	2D-hydro	1–10	ESM	Regional/ ESM	–	TS	1 ESM 1 SSP	Fine scale storm surge, SLR
Optimal	2D-hydro-Waves	1–5	Downscale	Regional	–	T	2 ESM 2 SSP	Extreme waves, Multiple storylines
Optimal	3D-hydro	1–5	Downscale	Regional	Hydrol	T	2 ESM 2 SSP	Component interaction, Multiple storylines
Advanced	RCM-Waves	1–5	O-A coupled	Regional	Hydrol	T	2 + ESM 3 + SSP	Dynamically consistent response, Uncertainty budget
Also consider	Unstructured grids. Erosion. Interactive wave coupling							
Local	**Model**	**Scale (km)**	**Atmos Forcing**	**Ocean Forcing**	**Land Forcing**	**Sim**	**Ensemble**	**Application**
Acceptable	2D-hydro	0.1–1	Downscale	Regional/ Sub-regional	–	TS	1 ESM 1 SSP	Local detail for storm surge, SLR
Optimal	2D-unstructured Waves	0.05–0.1	Downscale	Sub-regional	–	TS	2 ESM 2 SSP	Urban scale impacts, Extreme waves
Optimal	3D-hydro	0.5–1	Downscale	Sub-regional	Hydro-Model	TS	1 ESM 1 SSP	Local detail for storm surge, SLR, Component interaction
Advanced	RCM-Waves	0.05–0.1	O-A coupled	Sub-regional	Hydro-Model	TS	2 + ESM 3 + SSP	Dynamically consistent response, Uncertainty budget
Also consider	Erosion. Interactive wave coupling. Inundation modelling. BGC							

and as FLAME is not a directly funded activity, the suggestions here are aspirational, depending on the resources that can be captured to realise this. Here we only describe a high-level framework. In practice extensive technical details of each component are required to produce actionable protocols. Developing consensus on these will be subject of future workshops and discussion forums. Specifically, these would be organised around protocol development themes that cut across the four strands:

i. Climate-ocean dynamical downscaling
ii. Coastal and estuarine downscaling
iii. Biogeochemistry and ecosystem modelling
iv. User perspectives

Care is needed to align GCO-MIP with other activity in this area, specifically the CLIVAR-CORDEX-Ocean task force on regional ocean modelling and climate projections. Given its connection to WCRP and CORDEX, it is appropriate that that group defines the regional domain scheme, specifically targeting IPCC Assessment Reports, and GCO-MIP builds on that scheme across scales from regional to local, targeting end-user requirements. On this basis, we would aim to harmonise the protocol development with the CLIVAR-CORDEX-Ocean TF, e.g. with joint workshops, particularly on (i) Climate-ocean dynamical downscaling.

Strand 1: Common *meta*-data, assessment, diagnostics and best practice

Any downscaled coastal ocean model experiment with freely accessible data and code would be able to participate. A common simulation *meta*-data template would be used to fully and accurately describe the simulations and output. These include either a publication or a repository (e.g. Zenodo) with a DOI. Ideally, step-by-step instructions to reproduce the simulation would be provided (e.g. as in Polton et al., 2022). A standard set of minimal outputs would be prescribed that includes a set of standard validation metrics against global observational data sets. Best practice validation approaches with any available regional data would also be described. Scripts to produce these would also be provided. Global forced models can participate in this strand providing data either globally or for selected regions.

An on-line repository would be provided to collate and share the *meta*-data and assessment, with a web-map of domains and links to the repository where the common output is available.

A live on-line, interactive, best practice guide would be provided. This spans the various applications described in this paper and includes both the current state-of-the-art (as described here) and opportunities for up-date and comment based on emerging practitioner experience. It includes both the rationale behind the strands, and more technical considerations of best practice, e.g. how to treat riverine inputs, missing biogeochemical variables, and interactions at the sediment interface.

Strand 2: Standard model experiments

GCO-MIP specifies, and makes available, a standard set of forcing data, covering a small number of forcing ESMs and SSP scenarios; this defines the minimal simulation ensemble and covers *Acceptable* and *Optimal* options in Tables 1 and 2. The forcing data include atmosphere, ocean and hydrological components, and are selected to perform acceptably in all ocean basins. They include options with biogeochemical variables and without (generally from higher resolution ESMs). Downscaled simulations without a biogeochemical model would ideally run both sets. Global ocean forced models with biogeochemistry would be encouraged to participate in this strand to allow the regional downscaling models with biogeochemistry to include the higher resolution ESMs without marine ecosystems. Scripts for boundary condition preparation for commonly used regional ocean models would be provided. Standard bias correction algorithms would also be provided, but left to the participant to use or not depending on their requirements and assessment. The simulation period is specified as both the start and end date for a transient simulation and as time-slices. For time-slices we specify present, mid-century, and end of century 30-year periods. For each forcing dataset and ocean basin we identify shorter 5- and 10-year periods where the mean for key forcing variables most closely matches the mean of the 30-year period. This is to facilitate modelling at the sub-regional and local scale, where transient simulations may not be practical. These simulations can be run for any region and at any scale (but guided by Tables 1 and 2), in forced or coupled mode, with or without a terrestrial input model. Common model *meta*-data, output and assessment follows Strand 1.

Example machine learning approaches to develop emulators for these dynamical simulations would be provided. This would allow participants to readily expand their ensembles and better explore uncertainty.

Strand 3: Common model regions and local case studies

This strand has two elements: The CLIVAR-CORDEX-Ocean TF will define a set of regional scale domains, which provide the GCO-MIP regional-scale domains with global coverage. Alongside this, GCO-MIP specifies a set of exemplar case studies downscaled from the regional domains at sub-regional and local scale. These will align with GlobalCoast Pilot sites, with suggested minimal resolution for each (Tables 1 and 2). The three scales are nested within each other to allow incremental refinement from the coarser resolution global forcing data. Models that include a substantial fraction of a core region can be included in the strand; see (Golbeck et al., 2015) for an example of how multiple models with different but overlapping regions can be usefully compared. The set of case studies aims to span different coastal ocean types, based on a hydrodynamic-process based typology. Strand 3 domains run Strand 2 experiments, and the harmonisation of protocols would ideally mean that simulations at the regional scale would be able to contribute to both GCO-MIP and the CLIVAR-CORDEX-Ocean TF. Global forced models can participate in this strand providing data for the selected regions, most likely for the regional scale set. Common model *meta*-data, output and assessment follows strand 1. A catalogue of reproducible 'worked examples' for each case study would be developed. As these develop maturity their number can be expanded through increased participation, e.g. through the GlobalCoast Pilot sites network.

Strand 4: Data dissemination and end user communication

Best practice approaches for sharing data and communicating the outputs of coastal ocean downscaling to end users would be developed. Informative and engaging ways to analyse and disseminate the information would be co-developed with end user communities. These would include communicating the diverse range of regional response to climate change, the treatment of uncertainty and the use of non-probabilistic (story-line) approaches. A hierarchical approach to data sharing would be developed to meet multiple end user needs, from raw model data through to synthesised information products. Given the diverse range of end users, removed from the science and technical aspects, it is expected that this would occur via a community of *intermediate users*, who would develop bespoke climate information services for specific end-user groups. This would be developed through the outcomes of User Perspective workshops and supported by the GlobalCoast cloud infrastructure framework. Hence it is expected that this hierarchy of data sharing become more user-specific as it evolves away from raw model data. However, coordinating best practice across this data translation process would be important and enable the development of more standard information products in some cases.

Together, these four strands would produce a coherent collection of accurately and consistently described future climate downscaling simulations crossing scales from regional to local. Strand 1 alone offers a substantial step forward from the current, *ad hoc* and disparate approach to downscaling model description. Strand 3 provides crucial, and novel, insight on downscaling model uncertainty across scales, linking with the CLIVAR-CORDEX-Ocean TF. Strands 1 and 2 would allow cross-regional comparison and assessment of climate change impacts, in a systematic way. Except in global cases or coordinated multi-region experiments (Barange et al., 2014), model differences inevitably contaminate the comparison [as in Holt et al. 2016]; however, Strand 3 provides some information on this.

7. Closing remarks

In this paper we have explored the challenges related to developing future climate impact information in the global coastal ocean across multiple societal challenges, such as coastal hazards, marine ecosystems and the marine economy. It is clear from this study that future climate downscaling in the coastal ocean is extremely challenging, both technically and conceptually, since there are multiple modelling trade-offs and choices. The need for cross-sectoral expertise (e.g. in regional atmospheric and land surface/hydrological modelling) is seen as a key challenge and barrier to entry for fully sea-air-land coupled approaches, which would be considered the ideal. An internationally coordinated approach, in the context of the UN Decade of Ocean Science for Sustainable Development, is explored and building connections across diverse community of practices is a particular opportunity of this. The vision of GCO-MIP is multiple coordinated regional downscaled models with global coverage, aligned forced global ocean-sea ice models, and a growing set of coordinated sub-regional to local scale case studies. The success of such an endeavour would be judged both on the added value over the Global Climate and Earth System Models of CMIP, in terms of more accurate process representation and geographic detail, and on the improved information and advice available to end users. A collective approach is highly beneficial, particularly with the development of partnerships between less experienced practitioners and end users and more established groups to enable capacity building and increase uptake of information.

Funding sources

This work was supported by the: NERC NC International Science project FOCUS (NE/X006271/1), NERC-funded CHAMFER (NE/W004992/1) and CANARI (NE/W004984/1) projects, UKRI-funded Co-Opt project (NE/V016423/1), NERC SEARCH project (NE/V004239/1). LC and FM acknowledge the funding from projects HyBay (PID2022-141181OB-I00, Spanish Ministry of Science, Innovation and Universities) and Perfect-Storm (2023/TCN/003 – Cantabria Government/FEDER, UE). LC acknowledges the funding from the Juan de la Cierva – Formación FJC2021-046933-I. IV acknowledges the support of Croatian Science Foundation (Grant IP-2022-10-9139, project C3PO, and IP-2022-10-306, project GLOMETS) and Interreg IT-HR project AdriaClimPlus. CL and JS acknowledge the funding of R+ postdoctoral fellowship from CSIRO research Office.

CRediT authorship contribution statement

Jason Holt: Writing – review & editing, Writing – original draft, Conceptualization. **Anna Katavouta:** Writing – review & editing, Writing – original draft, Visualization, Conceptualization. **Joanne Hopkins:** Writing – review & editing, Writing – original draft, Conceptualization. **Laurent O. Amoudry:** Writing – review & editing, Writing – original draft. **Christian M. Appendini:** Writing – review &

editing, Writing – original draft. **Lars Arneborg:** Writing – review & editing, Writing – original draft. **Alex Arnold:** Writing – review & editing, Writing – original draft. **Yuri Artioli:** Writing – review & editing, Writing – original draft. **Jerome Aucan:** Writing – review & editing, Writing – original draft. **Barbara Berx:** Writing – review & editing, Writing – original draft. **Laura Cagigal:** Writing – review & editing, Writing – original draft. **Michela De Dominicis:** Writing – review & editing, Writing – original draft. **Cléa Denamiel:** Writing – review & editing, Writing – original draft. **Giovanni Galli:** Writing – review & editing, Writing – original draft. **Jennifer A. Graham:** Writing – review & editing, Writing – original draft. **Zoe Jacobs:** Writing – review & editing, Writing – original draft. **Svetlana Jevrejeva:** Writing – review & editing, Writing – original draft. **Bahareh Kamranzad:** Writing – review & editing, Writing – original draft. **Clothilde Langlais:** Writing – review & editing, Writing – original draft. **Morten Andreas Dahl Larsen:** Writing – review & editing, Writing – original draft. **Andrea Lira-Loarca:** Writing – review & editing, Writing – original draft. **Charlotte Lyddon:** Writing – review & editing, Writing – original draft. **Moritz Mathis:** Writing – review & editing, Writing – original draft. **Angélique Melet:** Writing – review & editing, Writing – original draft. **Fernando Méndez:** Writing – review & editing, Writing – original draft. **Sanne Muis:** Writing – review & editing, Writing – original draft. **Paul Myers:** Writing – review & editing, Writing – original draft. **Mairéad O'Donovan:** Writing – review & editing. **Agnieszka Indiana Olbert:** Writing – review & editing, Writing – original draft. **Matthew D. Palmer:** Writing – review & editing, Writing – original draft. **Lachlan Phillips:** Writing – review & editing, Writing – original draft. **Jeff Polton:** Writing – review & editing, Writing – original draft. **Mercedes Pozo Buil:** Writing – review & editing, Writing – original draft. **Peter Robins:** Writing – review & editing, Writing – original draft. **Andrea Ruju:** Writing – review & editing, Writing – original draft. **Jodie A. Schlaefer:** Writing – review & editing, Writing – original draft. **Alfonso Senatore:** Writing – review & editing, Writing – original draft. **Samantha Siedlecki:** Writing – review & editing, Writing – original draft. **Jonathan Tinker:** Writing – review & editing, Writing – original draft. **Giorgia Verri:** Writing – review & editing, Writing – original draft. **Ivica Vilibić:** Writing – review & editing, Writing – original draft. **Xiaoyan Wei:** Writing – review & editing, Writing – original draft. **Nadia Pinardi:** Writing – review & editing, Writing – original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.pocean.2025.103497.

Data availability

No data was used for the research described in the article.

References

Aksenov, Y., Popova, E.E., Yool, A., Nurser, A.J.G., Williams, T.D., Bertino, L., Bergh, J., 2017. On the future navigability of Arctic sea routes: high-resolution projections of the Arctic Ocean and sea ice. *Mar. Policy* 75, 300–317. https://doi.org/10.1016/j.marpol.2015.12.027.

Alexander, M.A., Shin, S.-I., Scott, J.D., Curchitser, E., Stock, C., 2020. The response of the Northwest Atlantic Ocean to climate change. *J. Clim.* 33, 405–428. https://doi.org/10.1175/JCLI-D-19-0117.1.

Alvarez Fanjul, E., Ciliberti, S., Bahurel, P., 2022. Implementing operational ocean monitoring and forecasting systems. vol. GOOS-275: IOC-UNESCO. DOI: 10.48670/ETOOFS,.

Anderson, D.L., Ruggiero, P., Mendez, F.J., Barnard, P.L., Erikson, L.H., O'Neill, A.C., Merrifield, M., Rueda, A., Cagigal, L., Marra, J., 2021. Projecting climate dependent coastal flood risk with a hybrid statistical dynamical model. *Earth's Future* 9, e2021EF002285. https://doi.org/10.1029/2021EF002285.

Antolínez, J.A.A., Murray, A.B., Méndez, F.J., Moore, L.J., Farley, G., Wood, J., 2018. Downscaling changing coastlines in a changing climate: the hybrid approach. *J. Geophys. Res. Earth* 123, 229–251. https://doi.org/10.1002/2017JF004367.

Arns, A., Dangendorf, S., Jensen, J., Talke, S., Bender, J., Pattiaratchi, C., 2017. Sea-level rise induced amplification of coastal protection design heights. *Sci. Rep.* 7, 40171. https://doi.org/10.1038/srep40171.

Artioli, Y., Blackford, J.C., Nondal, G., Bellerby, R.G.J., Wakelin, S.L., Holt, J.T., Butenschön, M., 2014. Heterogeneity of impacts of high CO2 on the North Western European Shelf. *Biogeosciences* 11, 601–612.

Baird, M.E., Adams, M.P., Babcock, R.C., Oubelkheir, K., Mongin, M., Wild-Allen, K.A., Skerratt, J., Robson, B.J., Petrou, K., Ralph, P.J., O'Brien, K.R., Carter, A.B., Jarvis, J.C., Rasheed, M.A., 2016. A biophysical representation of seagrass growth for application in a complex shallow-water biogeochemical model. *Ecol. Model.* 325, 13–27. https://doi.org/10.1016/j.ecolmodel.2015.12.011.

Baird, M.E., Mongin, M., Skerratt, J., Margvelashvili, N., Tickell, S., Steven, A.D.L., Robillot, C., Ellis, R., Waters, D., Kaniewska, P., Brodie, J., 2021. Impact of catchment-derived nutrients and sediments on marine water quality on the Great Barrier Reef: an application of the eReefs marine modelling system. *Mar. Pollut. Bull.* 167, 112297. https://doi.org/10.1016/j.marpolbul.2021.112297.

Bakun, A., 1990. Global climate change and intensification of coastal ocean upwelling. *Science* 247, 198–201. https://doi.org/10.1126/science.247.4939.198.

Barange, M., Merino, G., Blanchard, J.L., Scholtens, J., Harle, J., Allison, E.H., Allen, J.I., Holt, J., Jennings, S., 2014. Impacts of climate change on marine ecosystem production in societies dependent on fisheries. *Nature Clim. Change* 4, 211–216. https://doi.org/10.1038/nclimate2119.

Bernier, N.B., Hemer, M., Mori, N., Appendini, C.M., Breivik, O., de Camargo, R., Casas-Prat, M., Duong, T.M., Haigh, I.D., Howard, T., Hernaman, V., Huizy, O., Irish, J.L., Kirezci, E., Kohno, N., Lee, J.-W., McInnes, K.L., Meyer, E.M.I., Marcos, M., Marsooli, R., Martin Oliva, A., Menendez, M., Moghimi, S., Muis, S., Polton, J.A., Pringle, W.J., Ranasinghe, R., Saillour, T., Smith, G., Tadesse, M.G., Swail, V., Tomoya, S., Voukouvalas, E., Wahl, T., Wang, P., Weisse, R., Westerink, J.J., Young, I., Zhang, Y.J., 2024. Storm surges and extreme sea levels: Review, establishment of model intercomparison and coordination of surge climate projection efforts (SurgeMIP). *Weather Clim. Extremes* 45, 100689. https://doi.org/10.1016/j.wace.2024.100689.

Berthou, S., Renshaw, R., Smyth, T., Tinker, J., Grist, J.P., Wihsgott, J.U., Jones, S., Inall, M., Nolan, G., Berx, B., Arnold, A., Blunn, L.P., Castillo, J.M., Cotterill, D., Daly, E., Dow, G., Gómez, B., Fraser-Leonhardt, V., Hirschi, J.J.M., Lewis, H.W., Mahmood, S., Worsfold, M., 2024. Exceptional atmospheric conditions in June 2023 generated a northwest European marine heatwave which contributed to breaking land temperature records. *Commun. Earth Environ.* 5, 287. https://doi.org/10.1038/s43247-024-01413-8.

Beusen, A.H.W., Doelman, J.C., Van Beek, L.P.H., Van Puijenbroek, P.J.T.M., Mogollón, J.M., Van Grinsven, H.J.M., Stehfest, E., Van Vuuren, D.P., Bouwman, A.F., 2022. Exploring river nitrogen and phosphorus loading and export to global coastal waters in the Shared Socio-economic pathways. *Glob. Environ. Chang.* 72, 102426. https://doi.org/10.1016/j.gloenvcha.2021.102426.

Bevacqua, E., De Michele, C., Manning, C., Couasnon, A., Ribeiro, A.F.S., Ramos, A.M., Vignotto, E., Bastos, A., Blesić, S., Durante, F., Hillier, J., Oliveira, S.C., Pinto, J.G., Ragno, E., Rivoire, P., Saunders, K., van der Wiel, K., Wu, W., Zhang, T., Zscheischler, J., 2021. Guidelines for studying diverse types of compound weather and climate events. *Earth's Future* 9, e2021EF002340. https://doi.org/10.1029/2021EF002340.

Bhatia, M.P., Waterman, S., Burgess, D.O., Williams, P.L., Bundy, R.M., Mellett, T., Roberts, M., Bertrand, E.M., 2021. Glaciers and nutrients in the canadian arctic archipelago marine system. *Global Biogeochem. Cycles* 35, e2021GB006976. https://doi.org/10.1029/2021GB006976.

Bishop, B., Oliver, E.C.J., Aporta, C., 2022. Co-producing maps as boundary objects: bridging Labrador Inuit knowledge and oceanographic research. *J. Cult. Geogr.* 39, 55–89. https://doi.org/10.1080/08873631.2021.1998992.

Blumberg, A., Bruno, M., 2018. *The Urban Ocean: The Interaction of Cities with Water*. Doi: 10.1017/9781108123839.

Bograd, S.J., Jacox, M.G., Hazen, E.L., Lovecchio, E., Montes, I., Pozo Buil, M., Shannon, L.J., Sydeman, W.J., Rykaczewski, R.R., 2023. Climate change impacts on eastern boundary upwelling systems. *Ann. Rev. Mar. Sci.* 15, 303–328. https://doi.org/10.1146/annurev-marine-032122-021945.

Bopp, L., Resplandy, L., Orr, J.C., Doney, S.C., Dunne, J.P., Gehlen, M., Halloran, P., Heinze, C., Ilyina, T., Séférian, R., Tjiputra, J., Vichi, M., 2013. Multiple stressors of ocean ecosystems in the 21st century: projections with CMIP5 models. *Biogeosciences* 10, 6225–6245. https://doi.org/10.5194/bg-10-6225-2013.

Brandenburg, K.M., Velthuis, M., Van de Waal, D.B., 2019. Meta-analysis reveals enhanced growth of marine harmful algae from temperate regions with warming and elevated CO2 levels. *Glob. Chang. Biol.* 25, 2607–2618. https://doi.org/10.1111/gcb.14678.

Braun, M., Thiombiano, A.N., Vieira, M.J.F., Stadnyk, T.A., 2021. Representing climate evolution in ensembles of GCM simulations for the Hudson Bay System. *Elem. Sci. Anth.* 9. https://doi.org/10.1525/elementa.2021.00011.

Breitburg, D., Levin, L.A., Oschlies, A., Grégoire, M., Chavez, F.P., Conley, D.J., Garçon, V., Gilbert, D., Gutiérrez, D., Isensee, K., Jacinto, G.S., Limburg, K.E., Montes, I., Naqvi, S.W.A., Pitcher, G.C., Rabalais, N.N., Roman, M.R., Rose, K.A., Seibel, B.A., Telszewski, M., Yasuhara, M., Zhang, J., 2018. Declining oxygen in the global ocean and coastal waters. *Science* 359. https://doi.org/10.1126/science.aam7240.

Bricheno, L., Yeo, I., Clare, M., Hunt, J., Griffiths, A., Carter, L., Talling, P.J., Baker, M., Wilson, S., West, M., Panuve, S., Fonua, S., 2024. The diversity, frequency and severity of natural hazard impacts on subsea telecommunications networks. *Earth Sci. Rev.* 259, 104972. https://doi.org/10.1016/j.earscirev.2024.104972.

Buchart, L., Castro de la Guardia, L., Xu, Y., Ridenour, N., Marson, J.M., Deschepper, I., Hamilton, A.K., Grivault, N., Myers, P.G., 2022. Future Climate Scenarios for Northern Baffin Bay and the Pikialasorsuaq (North Water Polynya) Region. *Atmos. Ocean* 60, 102–123. https://doi.org/10.1080/07055900.2022.2067028.

Byrne, D., Polton, J., O'Dea, E., Williams, J., 2023. Using the COAsT Python package to develop a standardised validation workflow for ocean physics models. *Geosci. Model Dev.*, 16, 3749–3764. https://doi.org/10.5194/gmd-16-3749-2023.

Cagigal, L., Méndez, F.J., Ricondo, A., Gutiérrez-Barceló, D., Bosserelle, C., Hoeke, R., 2024. BinWaves: an additive hybrid method to downscale directional wave spectra to nearshore areas. *Ocean Model.* 189, 102346. https://doi.org/10.1016/j.ocemod.2024.102346.

Camus, P., Mendez, F.J., Medina, R., 2011. A hybrid efficient method to downscale wave climate to coastal areas. *Coast. Eng.* 58, 851–862. https://doi.org/10.1016/j.coastaleng.2011.05.007.

Carmack, E., Winsor, P., Williams, W., 2015. The contiguous panarctic Riverine Coastal Domain: a unifying concept. *Prog. Oceanogr.* 139, 13–23. https://doi.org/10.1016/j.pocean.2015.07.014.

Castillo, J.M., Lewis, H.W., Mishra, A., Mitra, A., Polton, J., Brereton, A., Saulter, A., Arnold, A., Berthou, S., Clark, D., Crook, J., Das, A., Edwards, J., Feng, X., Gupta, A., Joseph, S., Klingaman, N., Momin, I., Pequignet, C., Sanchez, C., Saxby, J., Valdivieso da Costa, M., 2022. The Regional Coupled Suite (RCS-IND1): application of a flexible regional coupled modelling framework to the Indian region at kilometre scale. *Geosci. Model Dev.*, 15, 4193–4223. https://doi.org/10.5194/gmd-15-4193-2022.

Chaigneau, A.A., Law-Chune, S., Melet, A., Voldoire, A., Reffray, G., Aouf, L., 2023. Impact of sea level changes on future wave conditions along the coasts of western Europe. *Ocean Sci.* 19, 1123–1143. https://doi.org/10.5194/os-19-1123-2023.

Chaigneau, A.A., Reffray, G., Voldoire, A., Melet, A., 2022. IBI-CCS: a regional high-resolution model to simulate sea level in western Europe. *Geosci. Model Dev*, 15, 2035–2062. https://doi.org/10.5194/gmd-15-2035-2022.

Chust, G., Allen, J.I., Bopp, L., Schrum, C., Holt, J., Tsiaras, K., Zavatarell, M., Chifflet, M., Cannaby, H., Dadou, I., Daewel, U., Wakelin, S.L., Machu, E., Pushpadas, D., Butenschon, M., Artioli, Y., Petihakis, G., Smith, C., Garçon, V., Goubanova, K., Fach, B., Salihoglu, B., Clementi, E., Irigoien, X., 2014. Biomass changes and trophic amplification of plankton in a warmer ocean. *Glob. Chang. Biol.* 7, 2124–2139. https://doi.org/10.1111/gcb.12562.

Cloern, J.E., Abreu, P.C., Carstensen, J., Chauvaud, L., Elmgren, R., Grall, J., Greening, H., Johansson, J.O.R., Kahru, M., Sherwood, E.T., Xu, J., Yin, K., 2016. Human activities and climate variability drive fast-paced change across the world's estuarine–coastal ecosystems. *Glob. Chang. Biol.* 22, 513–529. https://doi.org/10.1111/gcb.13059.

Cooley, S., D. Schoeman, L. Bopp, P. Boyd, S. Donner, D.Y. Ghebrehiwet, S.-I. Ito, W. Kiessling, P. Martinetto, E. Ojea, M.-F. Racault, B. Rost, Skern-Mauritzen, M., 2023. Oceans and Coastal Ecosystems and Their Services. In C. Intergovernmental Panel on Climate (Ed.), *Climate Change 2022 – Impacts, Adaptation and Vulnerability: Working Group II Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (pp. 379-550). Cambridge: Cambridge University Press. DOI: 10.1017/9781009325844.005.

Couasnon, A., Eilander, D., Muis, S., Veldkamp, T.I.E., Haigh, I.D., Wahl, T., Winsemius, H.C., Ward, P.J., 2020. Measuring compound flood potential from river discharge and storm surge extremes at the global scale. *Nat. Hazards Earth Syst. Sci.*, 20, 489–504. https://doi.org/10.5194/nhess-20-489-2020.

Coxon, G., Freer, J., Lane, R., Dunne, T., Knoben, W.J.M., Howden, N.J.K., Quinn, N., Wagener, T., Woods, R., 2019. DECIPHeR v1: dynamic fluxEs and connectivity for predictions of hydrology. *Geosci. Model Dev.* 12, 2285–2306. https://doi.org/10.5194/gmd-12-2285-2019.

Dandapat, S., Gnanaseelan, C., Parekh, A., 2020. Impact of excess and deficit river runoff on Bay of Bengal upper ocean characteristics using an ocean general circulation model. *Deep Sea Res. Part II* 172, 104714. https://doi.org/10.1016/j.dsr2.2019.104714.

Danilov, S., 2013. Ocean modeling on unstructured meshes. *Ocean Model.* 69, 195–210. https://doi.org/10.1016/j.ocemod.2013.05.005.

De Dominicis, M., Wolf, J., Jevrejeva, S., Zheng, P., Hu, Z., 2020. Future interactions between sea level rise, tides, and storm surges in the world's largest Urban Area. *Geophys. Res. Lett.* 47, e2020GL087002. https://doi.org/10.1029/2020GL087002.

Denamiel, C., Belušić, D., Zemunik, P., Vilibić, I., 2023. Climate projections of meteotsunami hazards. *Front. Mar. Sci.* 10. https://doi.org/10.3389/fmars.2023.1167863.

Denamiel, C., Šepić, J., Ivanković, D., Vilibić, I., 2019. The Adriatic Sea and Coast modelling suite: evaluation of the meteotsunami forecast component. *Ocean Model.* 135, 71–93. https://doi.org/10.1016/j.ocemod.2019.02.003.

Dey, D., Marsh, R., Drijfhout, S., Josey, S.A., Sinha, B., Grist, J., Döös, K., 2024. Formation of the Atlantic Meridional Overturning Circulation lower limb is critically dependent on Atlantic-Arctic mixing. *Nat. Commun.* 15, 7341. https://doi.org/10.1038/s41467-024-51777-w.

Doney, S.C., Busch, D.S., Cooley, S.R., Kroeker, K.J., 2020. The impacts of ocean acidification on marine ecosystems and reliant human communities. *Annu. Rev. Environ. Resour.* 45, 83–112. https://doi.org/10.1146/annurev-environ-012320-083019.

Drenkard, E.J., Stock, C., Ross, A.C., Dixon, K.W., Adcroft, A., Alexander, M., Balaji, V., Bograd, S.J., Butenschön, M., Cheng, W., Curchitser, E., Lorenzo, E.D., Dussin, R., Haynie, A.C., Harrison, M., Hermann, A., Hollowed, A., Holsman, K., Holt, J., Jacox, M.G., Jang, C.J., Kearney, K.A., Muhling, B.A., Buil, M.P., Saba, V., Sandø, A. B., Tommasi, D., Wang, M., 2021. Next-generation regional ocean projections for living marine resource management in a changing climate. *ICES J. Mar. Sci.* https://doi.org/10.1093/icesjms/fsab100.

Dürr, H.H., Laruelle, G.G., van Kempen, C.M., Slomp, C.P., Meybeck, M., Middelkoop, H., 2011. Worldwide typology of nearshore coastal systems: defining the estuarine filter of river inputs to the oceans. *Estuar. Coasts* 34, 441–458. https://doi.org/10.1007/s12237-011-9381-y.

Echevin, V., Gévaudan, M., Espinoza-Morriberón, D., Tam, J., Aumont, O., Gutierrez, D., Colas, F., 2020. Physical and biogeochemical impacts of RCP8.5 scenario in the Peru upwelling system. *Biogeosciences* 17, 3317–3341. https://doi.org/10.5194/bg-17-3317-2020.

Evans, J.P., Belmadani, A., Menkes, C., Stephenson, T., Thatcher, M., Gibson, P.B., Peltier, A., 2024. Higher-resolution projections needed for small island climates. *Nat. Clim. Chang.* 14, 668–670. https://doi.org/10.1038/s41558-024-02028-9.

Eyring, V., Cox, P.M., Flato, G.M., Gleckler, P.J., Abramowitz, G., Caldwell, P., Collins, W.D., Gier, B.K., Hall, A.D., Hoffman, F.M., Hurtt, G.C., Jahn, A., Jones, C.D., Klein, S.A., Krasting, J.P., Kwiatkowski, L., Lorenz, R., Maloney, E., Meehl, G.A., Pendergrass, A.G., Pincus, R., Ruane, A.C., Russell, J.L., Sanderson, B.M., Santer, B. D., Sherwood, S.C., Simpson, I.R., Stouffer, R.J., Williamson, M.S., 2019. Taking climate model evaluation to the next level. *Nat. Clim. Chang.* 9, 102–110. https://doi.org/10.1038/s41558-018-0355-y.

FAO, 2022. *The State of World Fisheries and Aquaculture 2022. Towards Blue Transformation*. Rome: FAO. https://doi.org/10.4060/cc0461en.

Feng, D., Tan, Z., Engwirda, D., Wolfe, J.D., Xu, D., Liao, C., Bisht, G., Benedict, J.J., Zhou, T., Li, H.-Y., Leung, L.R., 2024. Simulation of compound flooding using river-ocean two-way coupled E3SM ensemble on variable-resolution meshes. *J. Adv. Model. Earth Syst.* 16, e2023MS004054. https://doi.org/10.1029/2023MS004054.

Fennel, K., Mattern, J.P., Doney, S.C., Bopp, L., Moore, A.M., Wang, B., Yu, L., 2022. Ocean biogeochemical modelling. *Nat. Rev. Methods Primers* 2, 76. https://doi.org/10.1038/s43586-022-00154-2.

Ferguson, G., Gleeson, T., 2012. Vulnerability of coastal aquifers to groundwater use and climate change. *Nat. Clim. Chang.* 2, 342–345. https://doi.org/10.1038/nclimate1413.

Flynn, K.J., Skibinski, D.O.F., 2020. Exploring evolution of maximum growth rates in plankton. *J. Plankton Res.* 42, 497–513. https://doi.org/10.1093/plankt/fbaa038.

Fox-Kemper, B., Hewitt, H.T., Xiao, C., Aðalgeirsdóttir, G., Drijfhout, S.S., Edwards, T.L., Golledge, N.R., Hemer, M.A., Kopp, R.E., Krinner, G., Mix, A., Notz, D., Nowicki, S., Nurhati, I.S., Ruiz, L., Sallee, J.-B., Slangen, A.B.A., Yu, Y., 2023. Ocean, Cryosphere and Sea Level Change. In C. Intergovernmental Panel on Climate (Ed.), *Climate Change 2021 – The Physical Science Basis: Working Group I Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (pp. 1211-1362). Cambridge: Cambridge University Press. DOI: 10.1017/9781009157896.011.

Frölicher, T.L., Fischer, E.M., Gruber, N., 2018. Marine heatwaves under global warming. *Nature* 560, 360–364. https://doi.org/10.1038/s41586-018-0383-9.

Fulton, C.J., Abesamis, R.A., Berkström, C., Depczynski, M., Graham, N.A.J., Holmes, T. H., Kulbicki, M., Noble, M.M., Radford, B.T., Tano, S., Tinkler, P., Wernberg, T., Wilson, S.K., 2019. Form and function of tropical macroalgal reefs in the Anthropocene. *Funct. Ecol.* 33, 989–999. https://doi.org/10.1111/1365-2435.13282.

Galli, G., Wakelin, S., Harle, J., Holt, J., Artioli, Y., 2024. Multi-model comparison of trends and controls of near-bed oxygen concentration on the northwest European continental shelf under climate change. *Biogeosciences* 21, 2143–2158. https://doi.org/10.5194/bg-21-2143-2024.

Gilbert, D., Rabalais, N.N., Díaz, R.J., Zhang, J., 2010. Evidence for greater oxygen decline rates in the coastal ocean than in the open ocean. *Biogeosciences* 7, 2283–2296. https://doi.org/10.5194/bg-7-2283-2010.

Giorgi, F., 2019. Thirty Years of Regional Climate Modeling: Where Are We and Where Are We Going next? *J. Geophys. Res. Atmos.* 124, 5696–5723. https://doi.org/10.1029/2018JD030094.

Golbeck, I., Li, X., Janssen, F., Brüning, T., Nielsen, J.W., Huess, V., Söderkvist, J., Büchmann, B., Siiriä, S.-M., Vähä-Piikkiö, O., Hackett, B., Kristensen, N.M., Engedahl, H., Blockley, E., Sellar, A., Lagemaa, P., Ozer, J., Legrand, S., Ljungemyr, P., Axell, L., 2015. Uncertainty estimation for operational ocean forecast products—a multi-model ensemble for the North Sea and the Baltic Sea. *Ocean Dyn.* 65, 1603–1631. https://doi.org/10.1007/s10236-015-0897-8.

Gómez-Navarro, J.J., Raible, C.C., García-Valero, J.A., Messmer, M., Montávez, J.P., Martius, O., 2022. Event selection for dynamical downscaling: a neural network approach for physically-constrained precipitation events. *Clim. Dyn.* 58, 2863–2879. https://doi.org/10.1007/s00382-019-04818-w.

Gopikrishna, B., Deo, M., 2019. Sediment transport and shoreline shifts in response to climate change at the tidal inlets of Chilika, India. *Proc. Inst. Mech. Eng. Part M* 233, 372–387. https://doi.org/10.1177/1475090217748755.

Gröger, M., Dieterich, C., Haapala, J., Ho-Hagemann, H.T.M., Hagemann, S., Jakacki, J., May, W., Meier, H.E.M., Miller, P.A., Rutgersson, A., Wu, L., 2021. Coupled regional Earth system modeling in the Baltic Sea region. *Earth Syst. Dyn.* 12, 939–973. https://doi.org/10.5194/esd-12-939-2021.

Haarsma, R.J., Roberts, M.J., Vidale, P.L., Senior, C.A., Bellucci, A., Bao, Q., Chang, P., Corti, S., Fučkar, N.S., Guemas, V., von Hardenberg, J., Hazeleger, W., Kodama, C., Koenigk, T., Leung, L.R., Lu, J., Luo, J.J., Mao, J., Mizielinski, M.S., Mizuta, R., Nobre, P., Satoh, M., Scoccimarro, E., Semmler, T., Small, J., von Storch, J.S., 2016. High Resolution Model Intercomparison Project (HighResMIP v1.0) for CMIP6. *Geosci. Model Dev.*, 9, 4185–4208. https://doi.org/10.5194/gmd-9-4185-2016.

Haigh, I.D., Pickering, M.D., Green, J.A.M., Arbic, B.K., Arns, A., Dangendorf, S., Hill, D. F., Horsburgh, K., Howard, T., Idier, D., Jay, D.A., Jänicke, L., Lee, S.B., Müller, M., Schindelegger, M., Talke, S.A., Wilmes, S.-B., Woodworth, P.L., 2020. The tides they are A-changin': a comprehensive review of past and future nonastronomical changes in tides, their driving mechanisms, and future implications. *Rev. Geophys.* 58, e2018RG000636. https://doi.org/10.1029/2018RG000636.

Hall, A., Cox, P., Huntingford, C., Klein, S., 2019. Progressing emergent constraints on future climate change. *Nat. Clim. Chang.* 9, 269–278. https://doi.org/10.1038/s41558-019-0436-6.

Hamlington, B.D., Gardner, A.S., Ivins, E., Lenaerts, J.T.M., Reager, J.T., Trossman, D.S., Zaron, E.D., Adhikari, S., Arendt, A., Aschwanden, A., Beckley, B.D., Bekaert, D.P.S., Blewitt, G., Caron, L., Chambers, D.P., Chandanpurkar, H.A., Christianson, K., Csatho, B., Cullather, R.I., DeConto, R.M., Fasullo, J.T., Frederikse, T., Freymueller, J.T., Gilford, D.M., Girotto, M., Hammond, W.C., Hock, R., Holschuh, N., Kopp, R.E., Landerer, F., Larour, E., Menemenlis, D., Merrifield, M., Mitrovica, J.X., Nerem, R.S., Nias, I.J., Nieves, V., Nowicki, S., Pangaluru, K., Piecuch, C.G., Ray, R.D., Rounce, D.R., Schlegel, N.-J., Seroussi, H., Shirzaei, M., Sweet, W.V., Velicogna, I., Vinogradova, N., Wahl, T., Wiese, D.N., Willis, M.J., 2020. Understanding of contemporary regional sea-level change and the implications for the future. *Rev. Geophys.* 58, e2019RG000672. https://doi.org/10.1029/2019RG000672.

Hao, J., Yuan, D., He, L., Yuan, H., Su, J., Pohlmann, T., Ran, X., 2024. Cross-shelf carbon transport in the east china sea and its future trend under global warming. *J. Geophys. Res. Oceans* 129, e2022JC019403. https://doi.org/10.1029/2022JC019403.

Hausfather, Z., Peters, G.P., 2020. Emissions–The "business as usual" story is misleading. *Ture* 577, 618–620. https://doi.org/10.1038/d41586-020-00177-3.

Hawkins, E., Sutton, R., 2009. The potential to narrow uncertainties in regional climate predictions. *Bull. Am. Meteorol. Soc.* 90, 1095–1107. https://doi.org/10.1175/2009BAMS2607.1.

Hemer, M.A., Wang, X.L., Weisse, R., Swail, V.R., 2012. Advancing wind-waves climate science: the COWCLIP project. *Bull. Am. Meteorol. Soc.* 93, 791–796. https://doi.org/10.1175/BAMS-D-11-00184.1.

Hermann, A.J., Gibson, G.A., Cheng, W., Ortiz, I., Aydin, K., Wang, M., Hollowed, A.B., Holsman, K.K., 2019. Projected biophysical conditions of the Bering Sea to 2100 under multiple emission scenarios. *ICES J. Mar. Sci.* 76, 1280–1304. https://doi.org/10.1093/icesjms/fsz043.

Hewitt, H.T., Roberts, M., Mathiot, P., Biastoch, A., Blockley, E., Chassignet, E.P., Fox-Kemper, B., Hyder, P., Marshall, D.P., Popova, E., Treguier, A.-M., Zanna, L., Yool, A., Yu, Y., Beadling, R., Bell, M., Kuhlbrodt, T., Arsouze, T., Bellucci, A., Castruccio, F., Gan, B., Putrasahan, D., Roberts, C.D., Van Roekel, L., Zhang, Q., 2020. Resolving and parameterising the ocean mesoscale in earth system models. *Curr. Clim. Change Rep.* 6, 137–152. https://doi.org/10.1007/s40641-020-00164-w.

Hinson, K.E., Friedrichs, M.A.M., Najjar, R.G., Herrmann, M., Bian, Z., Bhatt, G., St-Laurent, P., Tian, H., Shenk, G., 2023. Impacts and uncertainties of climate-induced changes in watershed inputs on estuarine hypoxia. *Biogeosciences* 20, 1937–1961. https://doi.org/10.5194/bg-20-1937-2023.

Hobday, A.J., Alexander, L.V., Perkins, S.E., Smale, D.A., Straub, S.C., Oliver, E.C.J., Benthuysen, J.A., Burrows, M.T., Donat, M.G., Feng, M., Holbrook, N.J., Moore, P.J., Scannell, H.A., Sen Gupta, A., Wernberg, T., 2016. A hierarchical approach to defining marine heatwaves. *Prog. Oceanogr.* 141, 227–238. https://doi.org/10.1016/j.pocean.2015.12.014.

Hoch, K.E., Petersen, M.R., Brus, S.R., Engwirda, D., Roberts, A.F., Rosa, K.L., Wolfram, P.J., 2020. MPAS-ocean simulation quality for variable-resolution North American coastal meshes. *J. Adv. Model. Earth Syst.* 12, e2019MS001848. https://doi.org/10.1029/2019MS001848.

Holbrook, N.J., Claar, D.C., Hobday, A.J., McInnes, K.L., Oliver, E.C.J., Gupta, A.S., Widlansky, M.J., Zhang, X., 2020. ENSO-driven ocean extremes and their ecosystem impacts. *El Niño Southern Oscillation in a Changing Climate* (pp. 409-428). DOI: 10.1002/9781119548164.ch18.

Holt, J., Butenschon, M., Wakelin, S.L., Artioli, Y., Allen, J.I., 2012. Oceanic controls on the primary production of the northwest European continental shelf: model experiments under recent past conditions and a potential future scenario. *Biogeosciences* 9, 97–117. https://doi.org/10.5194/bg-9-97-2012.

Holt, J., Harle, J., Proctor, R., Michel, S., Ashworth, M., Batstone, C., Allen, J.I., Holmes, R., Smyth, T., Haines, K., Bretherton, D., Smith, G., 2009. Modelling the global coastal-ocean. *Philos. Trans. R. Soc. Lon. A* 939–951. https://doi.org/10.1098/rsta.2008.0210.

Holt, J., Harle, J., Wakelin, S., Jardine, J., Hopkins, J., 2022. Why is seasonal density stratification in shelf seas expected to increase under future climate change? *Geophys. Res. Lett.* 49, e2022GL100448. https://doi.org/10.1029/2022GL100448.

Holt, J., Hyder, P., Ashworth, M., Harle, J., Hewitt, H.T., Liu, H., New, A.L., Pickles, S., Porter, A., Popova, E., Allen, J.I., Siddorn, J., Wood, R., 2017. Prospects for improving the representation of coastal and shelf seas in global ocean models. *Geosci. Model Dev.*, 10, 499–523. https://doi.org/10.5194/gmd-10-499-2017.

Holt, J., Polton, J., Huthnance, J., Wakelin, S., O'Dea, E., Harle, J., Yool, A., Artioli, Y., Blackford, J., Siddorn, J., Inall, M., 2018. Climate-driven change in the north atlantic and arctic oceans can greatly reduce the circulation of the North Sea. *Geophys. Res. Lett.* 45, 11,827–811,836. https://doi.org/10.1029/2018GL078878.

Holt, J., Schrum, C., Cannaby, H., Daewel, U., Allen, I., Artioli, Y., Bopp, L., Butenschon, M., Fach, B., Harle, J., Pushpadas, D., Salihoglu, B., Wakelin, S., 2016. Potential impacts of climate change on the primary production of regional seas: a comparative analysis of five European seas. *Prog. Oceanogr.* 140, 91–115.

Huthnance, J.M., 1995. Circulation, exchange and water masses at the ocean margin: the role of physical processes at the shelf edge. *Prog. Oceanogr.* 35, 353–431.

Iles, C.E., Vautard, R., Strachan, J., Joussaume, S., Eggen, B.R., Hewitt, C.D., 2020. The benefits of increasing resolution in global and regional climate simulations for European climate extremes. *Geosci. Model Dev.*, 13, 5583–5607. https://doi.org/10.5194/gmd-13-5583-2020.

Ilıcak, M., Drange, H., Wang, Q., Gerdes, R., Aksenov, Y., Bailey, D., Bentsen, M., Biastoch, A., Bozec, A., Böning, C., Cassou, C., Chassignet, E., Coward, A.C., Curry, B., Danabasoglu, G., Danilov, S., Fernandez, E., Fogli, P.G., Fujii, Y., Griffies, S.M., Iovino, D., Jahn, A., Jung, T., Large, W.G., Lee, C., Lique, C., Lu, J., Masina, S., George Nurser, A.J., Roth, C., Salas y Mélia, D., Samuels, B.L., Spence, P., Tsujino, H., Valcke, S., Voldoire, A., Wang, X., Yeager, S.G., 2016. An assessment of the Arctic Ocean in a suite of interannual CORE-II simulations. Part III: Hydrography and fluxes. *Ocean Model.* 100, 141–161. https://doi.org/10.1016/j.ocemod.2016.02.004.

IPCC, 2014. *Summary for policymakers. 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.* Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press.

IPCC, 2023. Summary for Policymakers. In V. Masson-Delmotte, P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M.I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J.B.R. Matthews, T.K. Maycock, T. Waterfield, O. Yelekçi, R. Yu, B. Zhou (Eds.), *Climate Change 2021 – The Physical Science Basis: Working Group I Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (pp. 3-32). Cambridge: Cambridge University Press. DOI: 10.1017/9781009157896.001.

Irwin, A.J., Finkel, Z.V., Müller-Karger, F.E., Troccoli Ghinaglia, L., 2015. Phytoplankton adapt to changing ocean environments. *Proc. Natl. Acad. Sci.* 112, 5762–5766. https://doi.org/10.1073/pnas.1414752112.

Iturbide, M., Gutiérrez, J.M., Alves, L.M., Bedia, J., Cerezo-Mota, R., Cimadevilla, E., Cofiño, A.S., Di Luca, A., Faria, S.H., Gorodetskaya, I.V., Hauser, M., Herrera, S., Hennessy, K., Hewitt, H.T., Jones, R.G., Krakovska, S., Manzanas, R., Martínez-Castro, D., Narisma, G.T., Nurhati, I.S., Pinto, I., Seneviratne, S.I., van den Hurk, B., Vera, C.S., 2020. An update of IPCC climate reference regions for subcontinental analysis of climate model data: definition and aggregated datasets. *Earth Syst. Sci. Data* 12, 2959–2970. https://doi.org/10.5194/essd-12-2959-2020.

Jevrejeva, S., Williams, J., Vousdoukas, M., Jackson, L., 2023. Future sea level rise dominates changes in worst case extreme sea levels along the global coastline by 2100. *Environ. Res. Lett.*

Jiang, S., Sweet, L.-B., Blougouras, G., Brenning, A., Li, W., Reichstein, M., Denzler, J., Shangguan, W., Yu, G., Huang, F., Zscheischler, J., 2024. How interpretable machine learning can benefit process understanding in the geosciences. *Earth's Future* 12, e2024EF004540. https://doi.org/10.1029/2024EF004540.

Jin, Y., Zhang, X., Church, J.A., Bao, X., 2021. Projected sea level changes in the marginal seas near China based on dynamical downscaling. *J. Clim.* 34, 7037–7055. https://doi.org/10.1175/JCLI-D-20-0796.1.

Joyce, B.R., Pringle, W.J., Wirasaet, D., Westerink, J.J., Van der Westhuysen, A.J., Grumbine, R., Feyen, J., 2019. High resolution modeling of western Alaskan tides and storm surge under varying sea ice conditions. *Ocean Model.* 141, 101421. https://doi.org/10.1016/j.ocemod.2019.101421.

Kavanaugh, M.T., Oliver, M.J., Chavez, F.P., Letelier, R.M., Muller-Karger, F.E., Doney, S. C., 2016. Seascapes as a new vernacular for pelagic ocean monitoring, management and conservation. *ICES J. Mar. Sci.* 73, 1839–1850. https://doi.org/10.1093/icesjms/fsw086.

Kelley, E., Sherman, K., 2018. Trends of the large marine ecosystem assessment and management approach as reflected in the literature. *Ocean Coast. Manag.* 155, 104–112. https://doi.org/10.1016/j.ocecoaman.2017.12.008.

Kelly, S., Popova, E., Yool, A., Jebri, F., Oliver, S., Srokosz, M., 2025. Abrupt changes in the timing and magnitude of the north atlantic bloom over the 21st century. *J. Geophys. Res. Oceans* 130, e2024JC022284. https://doi.org/10.1029/2024JC022284.

Kelly, S.J., Popova, E., Aksenov, Y., Marsh, R., Yool, A., 2020. They came from the pacific: how changing arctic currents could contribute to an ecological regime shift in the Atlantic Ocean. *Earth's Future* 8, e2019EF001394. https://doi.org/10.1029/2019EF001394.

Kern, S., McGuinn, M.E., Smith, K.M., Pinardi, N., Niemeyer, K.E., Lovenduski, N.S., Hamlington, P.E., 2024. Computationally efficient parameter estimation for high-dimensional ocean biogeochemical models. *Geosci. Model Dev.* 17, 621–649. https://doi.org/10.5194/gmd-17-621-2024.

Kirezci, E., Young, I.R., Ranasinghe, R., Muis, S., Nicholls, R.J., Lincke, D., Hinkel, J., 2020. Projections of global-scale extreme sea levels and resulting episodic coastal flooding over the 21st Century. *Sci. Rep.* 10, 11629. https://doi.org/10.1038/s41598-020-67736-6.

Kochkov, D., Yuval, J., Langmore, I., Norgaard, P., Smith, J., Mooers, G., Klöwer, M., Lottes, J., Rasp, S., Düben, P., Hatfield, S., Battaglia, P., Sanchez-Gonzalez, A., Willson, M., Brenner, M.P., Hoyer, S., 2024. Neural general circulation models for weather and climate. *Nature* 632, 1060–1066. https://doi.org/10.1038/s41586-024-07744-y.

Kondolf, G.M., Schmitt, R.J.P., Carling, P., Darby, S., Arias, M., Bizzi, S., Castelletti, A., Cochrane, T.A., Gibson, S., Kummu, M., Oeurng, C., Rubin, Z., Wild, T., 2018. Changing sediment budget of the Mekong: Cumulative threats and management strategies for a large river basin. *Sci. Total Environ.* 625, 114–134. https://doi.org/10.1016/j.scitotenv.2017.11.361.

Kulp, S.A., Strauss, B.H., 2019. New elevation data triple estimates of global vulnerability to sea-level rise and coastal flooding. *Nat. Commun.* 10, 4844. https://doi.org/10.1038/s41467-019-12808-z.

Kwiatkowski, L., Aumont, O., Bopp, L., Ciais, P., 2018. The impact of variable phytoplankton stoichiometry on projections of primary production, food quality, and carbon uptake in the global ocean. *Global Biogeochem. Cycles* 32, 516–528. https://doi.org/10.1002/2017GB005799.

Kwiatkowski, L., Torres, O., Bopp, L., Aumont, O., Chamberlain, M., Christian, J.R., Dunne, J.P., Gehlen, M., Ilyina, T., John, J.G., Lenton, A., Li, H., Lovenduski, N.S., Orr, J.C., Palmieri, J., Santana-Falcón, Y., Schwinger, J., Séférian, R., Stock, C.A., Tagliabue, A., Takano, Y., Tjiputra, J., Toyama, K., Tsujino, H., Watanabe, M., Yamamoto, A., Yool, A., Ziehn, T., 2020. Twenty-first century ocean warming, acidification, deoxygenation, and upper-ocean nutrient and primary production decline from CMIP6 model projections. *Biogeosciences* 17, 3439–3470. https://doi.org/10.5194/bg-17-3439-2020.

Le Traon, P.Y., Reppucci, A., Alvarez Fanjul, E., Aouf, L., Behrens, A., Belmonte, M., Bentamy, A., Bertino, L., Brando, V.E., Kreiner, M.B., Benkiran, M., Carval, T., Ciliberti, S.A., Claustre, H., Clementi, E., Coppini, G., Cossarini, G., De Alfonso Alonso-Muñoyerro, M., Delamarche, A., Dibarboure, G., Dinessen, F., Drevillon, M., Drillet, Y., Faugere, Y., Fernández, V., Fleming, A., Garcia-Hermosa, M.I., Sotillo, M. G., Garric, G., Gasparin, F., Giordan, C., Gehlen, M., Gregoire, M.L., Guinehut, S., Hamon, M., Harris, C., Hernandez, F., Hinkler, J.B., Hoyer, J., Karvonen, J., Kay, S., King, R., Lavergne, T., Lemieux-Dudon, B., Lima, L., Mao, C., Martin, M.J., Masina, S., Melet, A., Buongiorno Nardelli, B., Nolan, G., Pascual, A., Pistoia, J., Palazov, A., Piolle, J.F., Pujol, M.I., Pequignet, A.C., Peneva, E., Pérez Gómez, B., Petit de la Villeon, L., Pinardi, N., Pisano, A., Pouliquen, S., Reid, R., Remy, E., Santoleri, R., Siddorn, J., She, J., Staneva, J., Stoffelen, A., Tonani, M., Vandenbulcke, L., von Schuckmann, K., Volpe, G., Wettre, C., Zacharioudaki, A., 2019. From observation to information and users: the copernicus marine service perspective. *Front. Mar. Sci.* 6–2019. https://doi.org/10.3389/fmars.2019.00234.

Lenton, A., Matear, R.J., Keller, D.P., Scott, V., Vaughan, N.E., 2018. Assessing carbon dioxide removal through global and regional ocean alkalinization under high and low emission pathways. *Earth Syst. Dyn.*, 9, 339–357. https://doi.org/10.5194/esd-9-339-2018.

Lewis, H.W., Castillo Sanchez, J.M., Arnold, A., Fallmann, J., Saulter, A., Graham, J., Bush, M., Siddorn, J., Palmer, T., Lock, A., Edwards, J., Bricheno, L., Martínez-de la Torre, A., Clark, J., 2019. The UKC3 regional coupled environmental prediction system. *Geosci. Model Dev.*, 12, 2357–2400. https://doi.org/10.5194/gmd-12-2357-2019.

Lira-Loarca, A., Besio, G., 2022. Future changes and seasonal variability of the directional wave spectra in the Mediterranean Sea for the 21st century. *Environ. Res. Lett.* 17, 104015. https://doi.org/10.1088/1748-9326/ac8ec4.

Liu, X., Dunne, J., Stock, C., Harrison, M., Adcroft, A., Resplandy, L., 2019. Simulating water residence time in the coastal ocean: a global perspective. *Geophys. Res. Lett.* 46, 13910–13919. https://doi.org/10.1029/2019GL085097.

Liu, Y., Xie, L., Morrison, J.M., Kamykowski, D., 2013. Dynamic downscaling of the impact of climate change on the ocean circulation in the Galápagos Archipelago. *Adv. Meteorol.* 2013, 837432. https://doi.org/10.1155/2013/837432.

Liu, Z.-J., Minobe, S., Sasaki, Y.N., Terada, M., 2016. Dynamical downscaling of future sea level change in the western North Pacific using ROMS. *J. Oceanogr.* 72, 905–922. https://doi.org/10.1007/s10872-016-0390-0.

Lok, C.C.F., Chan, J.C.L., Toumi, R., 2022. Importance of air-sea coupling in simulating tropical cyclone intensity at landfall. *Adv. Atmos. Sci.* 39, 1777–1786. https://doi.org/10.1007/s00376-022-1326-9.

Longhurst, A., 1998. *Ecological Geography of the Sea*. Academic Press, San Diego and London.

Luijendijk, E., Gleeson, T., Moosdorf, N., 2020. Fresh groundwater discharge insignificant for the world's oceans but important for coastal ecosystems. *Nat. Commun.* 11, 1260. https://doi.org/10.1038/s41467-020-15064-8.

Lukovich, J.V., Jafarikhasragh, S., Myers, P.G., Ridenour, N.A., de la Guardia, L.C., Hu, X., Grivault, N., Marson, J., Pennelly, C., Stroeve, J.C., Sydor, K., Wong, K., Stadnyk, T.A., Barber, D.G., 2021. Simulated impacts of relative climate change and river discharge regulation on sea ice and oceanographic conditions in the Hudson Bay Complex. *Elementa: Sci. Anthropocene* 9. 10.1525/elementa.2020.00127.

Luneva, M.V., Ivanov, V.V., Tuzov, F., Aksenov, Y., Harle, J.D., Kelly, S., Holt, J.T., 2020. Hotspots of dense water cascading in the arctic ocean: implications for the pacific water pathways. *J. Geophys. Res. Oceans* 125, e2020JC016044. https://doi.org/10.1029/2020JC016044.

Lyddon, C., Chien, N., Vasilopoulos, G., Ridgill, M., Moradian, S., Olbert, A., Coulthard, T., Barkwith, A., Robins, P., 2024. Thresholds for estuarine compound flooding using a combined hydrodynamic–statistical modelling approach. *Nat. Hazards Earth Syst. Sci.*, 24, 973–997. https://doi.org/10.5194/nhess-24-973-2024.

Maggiorano, A., Baird, M., Langlais, C., Mongin, M., Skerratt, J., 2025. Impact of phytoplankton, CDOM, and suspended sediments on the vertical attenuation of light, changing heat content and circulation on a continental shelf: a modelling study of the Great Barrier Reef. *Ocean Model.* 193, 102465. https://doi.org/10.1016/j.ocemod.2024.102465.

Mathis, M., Elizalde, A., Mikolajewicz, U., 2019. The future regime of Atlantic nutrient supply to the Northwest European Shelf. *J. Mar. Syst.* 189, 98–115. https://doi.org/10.1016/j.jmarsys.2018.10.002.

Mathis, M., Lacroix, F., Hagemann, S., Nielsen, D.M., Ilyina, T., Schrum, C., 2024. Enhanced CO2 uptake of the coastal ocean is dominated by biological carbon fixation. *Nat. Clim. Chang.* 14, 373–379. https://doi.org/10.1038/s41558-024-01956-w.

Mathis, M., Logemann, K., Maerz, J., Lacroix, F., Hagemann, S., Chegini, F., Ramme, L., Ilyina, T., Korn, P., Schrum, C., 2022. Seamless integration of the coastal ocean in global marine carbon cycle modeling. *J. Adv. Model. Earth Syst.* 14, e2021MS002789. https://doi.org/10.1029/2021MS002789.

Mayer, B., Mathis, M., Mikolajewicz, U., Pohlmann, T., 2022. RCP8.5-projected changes in German Bight storm surge characteristics from regionalized ensemble simulations for the end of the twenty-first century. *Front. Clim.* 4. Doi:10.3389/fclim.2022.992119.

Melet, A., Almar, R., Hemer, M., Le Cozannet, G., Meyssignac, B., Ruggiero, P., 2020. Contribution of wave setup to projected coastal sea level changes. *J. Geophys. Res. Oceans* 125, e2020JC016078. https://doi.org/10.1029/2020JC016078.

Meredith, E.P., Semenov, V.A., Maraun, D., Park, W., Chernokulsky, A.V., 2015. Crucial role of black sea warming in amplifying the 2012 krymsk precipitation extreme. *Nat. Geosci.* 8, 615–619. https://doi.org/10.1038/ngeo2483.

Middelburg, J.J., Soetaert, K., Hagens, M., 2020. Ocean Alkalinity, Buffering and Biogeochemical Processes. *Rev. Geophys.* 58, e2019RG000681. https://doi.org/10.1029/2019RG000681.

Miller, M.W., 2015. Coral Disturbance and Recovery in a Changing World. In C. Birkeland (Ed.), *Coral Reefs in the Anthropocene* (pp. 217-230). Dordrecht: Springer Netherlands. 10.1007/978-94-017-7249-5_11.

Mitra, A., Flynn, K.J., Burkholder, J.M., Berge, T., Calbet, A., Raven, J.A., Granéli, E., Glibert, P.M., Hansen, P.J., Stoecker, D.K., Thingstad, F., Tillmann, U., Våge, S., Wilken, S., Zubkov, M.V., 2014. The role of mixotrophic protists in the biological carbon pump. *Biogeosciences* 11, 995–1005. https://doi.org/10.5194/bg-11-995-2014.

Moore, S.K., Johnstone, J.A., Banas, N.S., Salathé, E.P., 2015. Present-day and future climate pathways affecting Alexandrium blooms in Puget Sound, WA, USA. *Harmful Algae* 48, 1–11. https://doi.org/10.1016/j.hal.2015.06.008.

Moriarty, J.M., Friedrichs, M.A.M., Harris, C.K., 2021. Seabed resuspension in the chesapeake bay: implications for biogeochemical cycling and hypoxia. *Estuar. Coasts* 44, 103–122. https://doi.org/10.1007/s12237-020-00763-8.

Morim, J., Hemer, M., Wang, X.L., Cartwright, N., Trenham, C., Semedo, A., Young, I., Bricheno, L., Camus, P., Casas-Prat, M., Erikson, L., Mentaschi, L., Mori, N., Shimura, T., Timmermans, B., Aarnes, O., Breivik, Ø., Behrens, A., Dobrynin, M., Menendez, M., Staneva, J., Wehner, M., Wolf, J., Kamranzad, B., Webb, A., Stopa, J., Andutta, F., 2019. Robustness and uncertainties in global multivariate wind-wave climate projections. *Nat. Clim. Chang.* 9, 711–718. https://doi.org/10.1038/s41558-019-0542-5.

Muilwijk, M., Hattermann, T., Martin, T., Granskog, M.A., 2024. Future sea ice weakening amplifies wind-driven trends in surface stress and Arctic Ocean spin-up. *Nat. Commun.* 15, 6889. https://doi.org/10.1038/s41467-024-50874-0.

Muis, S., Apecechea, M.I., Dullaart, J., de Lima Rego, J., Madsen, K.S., Su, J., Yan, K., Verlaan, M., 2020. A high-resolution global dataset of extreme sea levels, tides, and storm surges, including future projections. *Front. Mar. Sci.* 7. https://doi.org/10.3389/fmars.2020.00263.

Muis, S., Haigh, I.D., Guimarães Nobre, G., Aerts, J.C.J.H., Ward, P.J., 2018. Influence of El Niño-Southern Oscillation on Global Coastal Flooding. *Earth's Future* 6, 1311–1322. https://doi.org/10.1029/2018EF000909.

Murray, J.W., Top, Z., Özsoy, E., 1991. Hydrographic properties and ventilation of the Black Sea. *Deep Sea Research Part A. Oceanographic Research Papers* 38, S663–S689. https://doi.org/10.1016/S0198-0149(10)80003-2.

Myers, P.G., Barber, D., Braun, M., Buchart, L., de la Guardia, L.C., Deschepper, I., Dupont, F., Ehn, J., Garcia-Quintana, Y., Gillard, L.C., Grivault, N., Hu, X., Kirillov, S.A., Jafarikhasragh, S., Lukovich, J., Maps, F., Marson, J.M., Papakyriakou, T., Pennelly, C., Ridenour, N., Stadnyk, T.A., Sydor, K., Tao, R., Tefs, A., Tremblay, J.-É., Xu, Y., 2024. An overview of the NEMO modelling for the BaySys project. *Elem. Sci. Anth.* 12. https://doi.org/10.1525/elementa.2022.00111.

Nishikawa, S., Wakamatsu, T., Ishizaki, H., Sakamoto, K., Tanaka, Y., Tsujino, H., Yamanaka, G., Kamachi, M., Ishikawa, Y., 2021. Development of high-resolution future ocean regional projection datasets for coastal applications in Japan. *Prog Earth Planet Sci* 8, 7. https://doi.org/10.1186/s40645-020-00399-z.

OceanVisions, MBARI, 2022. Answering critical questions about sinking macroalgae for carbon dioxide removal: a research framework to investigate sequestration efficacy and environmental impacts. Available online at: oceanvisions.org/seaweedresearch.

Oerder, V., Colas, F., Echevin, V., Codron, F., Tam, J., Belmadani, A., 2015. Peru-Chile upwelling dynamics under climate change. *J. Geophys. Res. Oceans* 120, 1152–1172. https://doi.org/10.1002/2014JC010299.

Olbert, Hartnett, M., 2010. Storms and surges in Irish coastal waters. *Ocean Model.* 34, 50–62. https://doi.org/10.1016/j.ocemod.2010.04.004.

Olbert, Nash, S., Cunnane, C., Hartnett, M., 2013. Tide–surge interactions and their effects on total sea levels in Irish coastal waters. *Ocean Dyn.* 63, 599–614. https://doi.org/10.1007/s10236-013-0618-0.

Oliver, M.J., Irwin, A.J., 2008. Objective global ocean biogeographic provinces. *Geophys. Res. Lett.* 35. https://doi.org/10.1029/2008GL034238.

Palmer, M.D., Gregory, J.M., Bagge, M., Calvert, D., Hagedoorn, J.M., Howard, T., Klemann, V., Lowe, J.A., Roberts, C.D., Slangen, A.B.A., Spada, G., 2020. Exploring the drivers of global and local sea-level change over the 21st century and beyond. *Earth's Future* 8, e2019EF001413. https://doi.org/10.1029/2019EF001413.

Palmer, M.D., Harrison, B.J., Gregory, J.M., Hewitt, H.T., Lowe, J.A., Weeks, J.H., 2024. A framework for physically consistent storylines of UK future mean sea level rise. *Clim. Change* 177, 106. https://doi.org/10.1007/s10584-024-03734-1.

Payo, A., Favis-Mortlock, D., Dickson, M., Hall, J.W., Hurst, M.D., Walkden, M.J.A., Townend, I., Ives, M.C., Nicholls, R.J., Ellis, M.A., 2017. Coastal Modelling Environment version 1.0: a framework for integrating landform-specific component models in order to simulate decadal to centennial morphological changes on complex coasts. *Geosci. Model Dev.* 10, 2715–2740. https://doi.org/10.5194/gmd-10-2715-2017.

Pershing, A.J., Mills, K.E., Dayton, A.M., Franklin, B.S., Kennedy, B.T., 2018. Evidence for adaptation from the 2016 marine heatwave in the northwest Atlantic ocean. *Oceanography* 31, 152–161.

Petton, S., Garnier, V., Caillaud, M., Debreu, L., Dumas, F., 2023. Using the two-way nesting technique AGRIF with MARS3D V11.2 to improve hydrodynamics and estimate environmental indicators. *Geosci. Model Dev.*, 16, 1191–1211. https://doi.org/10.5194/gmd-16-1191-2023.

Pickering, M.D., Horsburgh, K.J., Blundell, J.R., Hirschi, J.J.M., Nicholls, R.J., Verlaan, M., Wells, N.C., 2017. The impact of future sea-level rise on the global tides. *Cont. Shelf Res.* 142, 50–68. https://doi.org/10.1016/j.csr.2017.02.004.

Piecuch, C.G., Bittermann, K., Kemp, A.C., Ponte, R.M., Little, C.M., Engelhart, S.E., Lentz, S.J., 2018. River-discharge effects on United States Atlantic and Gulf coast sea-level changes. *Proc. Natl. Acad. Sci.* 115, 7729–7734. https://doi.org/10.1073/pnas.1805428115.

Pilcher, D.J., Cross, J.N., Hermann, A.J., Kearney, K.A., Cheng, W., Mathis, J.T., 2022. Dynamically downscaled projections of ocean acidification for the Bering Sea. *Deep Sea Res. Part II* 198, 105055. https://doi.org/10.1016/j.dsr2.2022.105055.

Planchat, A., Kwiatkowski, L., Bopp, L., Torres, O., Christian, J.R., Butenschön, M., Lovato, T., Séférian, R., Chamberlain, M.A., Aumont, O., Watanabe, M., Yamamoto, A., Yool, A., Ilyina, T., Tsujino, H., Krumhardt, K.M., Schwinger, J., Tjiputra, J., Dunne, J.P., Stock, C., 2023. The representation of alkalinity and the carbonate pump from CMIP5 to CMIP6 Earth system models and implications for the carbon cycle. *Biogeosciences* 20, 1195–1257. https://doi.org/10.5194/bg-20-1195-2023.

Polton, J., Harle, J., de Dominicis, M., Katavouta, A., 2022. NOC-MSM/SEAsia: SEAsia (v0.1.0). Zenodo. Doi: 10.5281/zenodo.6483233.

Polton, J., Harle, J., Holt, J., Katavouta, A., Partridge, D., Jardine, J., Wakelin, S., Rulent, J., Wise, A., Hutchinson, K., Byrne, D., Bruciaferri, D., O'Dea, E., De Dominicis, M., Mathiot, P., Coward, A., Yool, A., Palmieri, J., Lessin, G., Mayorga-Adame, C.G., Le Guennec, V., Arnold, A., Rousset, C., 2023. Reproducible and relocatable regional ocean modelling: fundamentals and practices. *Geosci. Model Dev.* 16, 1481–1510. https://doi.org/10.5194/gmd-16-1481-2023.

Popova, E., Vousden, D., Sauer, W.H.H., Mohammed, E.Y., Allain, V., Downey-Breedt, N., Fletcher, R., Gjerde, K.M., Halpin, P.N., Kelly, S., Obura, D., Pecl, G., Roberts, M., Raitsos, D.E., Rogers, A., Samoilys, M., Sumaila, U.R., Tracey, S., Yool, A., 2019. Ecological connectivity between the areas beyond national jurisdiction and coastal waters: Safeguarding interests of coastal communities in developing countries. *Mar. Policy* 104, 90–102. https://doi.org/10.1016/j.marpol.2019.02.050.

Popova, E., Yool, A., Coward, A.C., Dupont, F., Deal, C., Elliott, S., Hunke, E., Jin, M., Steele, M., Zhang, J., 2012. What controls primary production in the Arctic Ocean? Results from an intercomparison of five general circulation models with biogeochemistry. *J. Geophys. Res. Oceans* 117. https://doi.org/10.1029/2011JC007112.

Powley, H.R., Polimene, L., Torres, R., Al Azhar, M., Bell, V., Cooper, D., Holt, J., Wakelin, S., Artioli, Y., 2024. Modelling terrigenous DOC across the north west European Shelf: Fate of riverine input and impact on air-sea CO2 fluxes. *Sci. Total Environ.* 912, 168938. https://doi.org/10.1016/j.scitotenv.2023.168938.

Pozo Buil, M., Fiechter, J., Jacox, M.G., Bograd, S.J., Alexander, M.A., 2023. Evaluation of different bias correction methods for dynamical downscaled future projections of the california current upwelling system. *Earth Space Sci.* 10, e2023EA003121. https://doi.org/10.1029/2023EA003121.

Pozo Buil, M., Jacox, M.G., Fiechter, J., Alexander, M.A., Bograd, S.J., Curchitser, E.N., Edwards, C.A., Rykaczewski, R.R., Stock, C.A., 2021. A dynamically downscaled ensemble of future projections for the california current system. *Front. Mar. Sci.* 8. https://doi.org/10.3389/fmars.2021.612874.

Proshutinsky, A., Steele, M., Timmermans, M.-L., 2016. Forum for arctic modeling and observational synthesis (FAMOS): past, current, and future activities. *J. Geophys. Res. Oceans* 121, 3803–3819. https://doi.org/10.1002/2016JC011898.

Rahimi, S., Huang, L., Norris, J., Hall, A., Goldenson, N., Risser, M., Feldman, D.R., Lebo, Z.J., Dennis, E., Thackeray, C., 2024. Understanding the cascade: removing GCM biases improves dynamically downscaled climate projections. *Geophys. Res. Lett.* 51, e2023GL106264. https://doi.org/10.1029/2023GL106264.

Renault, L., Marchesiello, P., 2022. Ocean tides can drag the atmosphere and cause tidal winds over broad continental shelves. *Commun. Earth Environ.* 3, 70. https://doi.org/10.1038/s43247-022-00403-y.

Renault, L., McWilliams, J.C., Penven, P., 2017. Modulation of the Agulhas current retroflection and leakage by oceanic current interaction with the atmosphere in coupled simulations. *J. Phys. Oceanogr.* 47, 2077–2100. https://doi.org/10.1175/JPO-D-16-0168.1.

Resplandy, L., Hogikyan, A., Müller, J.D., Najjar, R.G., Bange, H.W., Bianchi, D., Weber, T., Cai, W.J., Doney, S.C., Fennel, K., Gehlen, M., Hauck, J., Lacroix, F., Landschützer, P., Le Quéré, C., Roobaert, A., Schwinger, J., Berthet, S., Bopp, L., Chau, T.T.T., Dai, M., Gruber, N., Ilyina, T., Kock, A., Manizza, M., Lachkar, Z., Laruelle, G.G., Liao, E., Lima, I.D., Nissen, C., Rödenbeck, C., Séférian, R., Toyama, K., Tsujino, H., Regnier, P., 2024. A synthesis of global coastal ocean greenhouse gas fluxes. *Global Biogeochem. Cycles* 38, e2023GB007803. https://doi.org/10.1029/2023GB007803.

Ricondo, A., Cagigal, L., Rueda, A., Hoeke, R., Storlazzi, C.D., Méndez, F.J., 2023. HyWaves: hybrid downscaling of multimodal wave spectra to nearshore areas. *Ocean Model.* 184, 102210. https://doi.org/10.1016/j.ocemod.2023.102210.

Rippeth, T., Fine, E., 2022. Turbulent mixing in a changing Arctic ocean. *Oceanography* 35. https://doi.org/10.5670/oceanog.2022.103.

Robinson, A.R., Brink, K. (Eds.), 2006. The Global Coastal Ocean: Interdisciplinary Regional Studies and Syntheses. Harvard University Press.

Robinson, L.M., Gledhill, D.C., Moltschaniwskyj, N.A., Hobday, A.J., Frusher, S., Barrett, N., Stuart-Smith, J., Pecl, G.T., 2015. Rapid assessment of an ocean warming hotspot reveals "high" confidence in potential species' range extensions. *Glob. Environ. Chang.* 31, 28–37. https://doi.org/10.1016/j.gloenvcha.2014.12.003.

Ross, A.C., Stock, C.A., Adcroft, A., Curchitser, E., Hallberg, R., Harrison, M.J., Hedstrom, K., Zadeh, N., Alexander, M., Chen, W., Drenkard, E.J., du Pontavice, H., Dussin, R., Gomez, F., John, J.G., Kang, D., Lavoie, D., Resplandy, L., Roobaert, A., Saba, V., Shin, S.I., Siedlecki, S., Simkins, J., 2023. A high-resolution physical–biogeochemical model for marine resource applications in the northwest Atlantic (MOM6-COBALT-NWA12 v1.0). *Geosci. Model Dev.*, 16, 6943–6985. https://doi.org/10.5194/gmd-16-6943-2023.

Rueda, A., Vitousek, S., Camus, P., Tomás, A., Espejo, A., Losada, I.J., Barnard, P.L., Erikson, L.H., Ruggiero, P., Reguero, B.G., Mendez, F.J., 2017. A global classification of coastal flood hazard climates associated with large-scale oceanographic forcing. *Sci. Rep.* 7, 5038. https://doi.org/10.1038/s41598-017-05090-w.

Ruti, P.M., Somot, S., Giorgi, F., Dubois, C., Flaounas, E., Obermann, A., Dell'Aquila, A., Pisacane, G., Harzallah, A., Lombardi, E., Ahrens, B., Akhtar, N., Alias, A., Arsouze, T., Aznar, R., Bastin, S., Bartholy, J., Béranger, K., Beuvier, J., Bouffies-Cloché, S., Brauch, J., Cabos, W., Calmanti, S., Calvet, J.C., Carillo, A., Conte, D., Coppola, E., Djurdjevic, V., Drobinski, P., Elizalde-Arellano, A., Gaertner, M., Galàn, P., Gallardo, C., Gualdi, S., Goncalves, M., Jorba, O., Jordà, G., L'Heveder, B., Lebeaupin-Brossier, C., Li, L., Liguori, G., Lionello, P., Maciàs, D., Nabat, P., Önol, B., Raikovic, B., Ramage, K., Sevault, F., Sannino, G., Struglia, M.V., Sanna, A., Torma, C., Vervatis, V., 2016. Med-CORDEX initiative for mediterranean climate studies. *Bull. Am. Meteorol. Soc.* 97, 1187–1208. https://doi.org/10.1175/BAMS-D-14-00176.1.

Rykaczewski, R.R., Dunne, J.P., 2010. Enhanced nutrient supply to the California current ecosystem with global warming and increased stratification in an earth system model. *Geophys. Res. Lett.* 37, L21606. https://doi.org/10.1029/2010gl045019.

Saccotelli, L., Verri, G., De Lorenzis, A., Cherubini, C., Caccioppoli, R., Coppini, G., Maglietta, R., 2024. Enhancing estuary salinity prediction: a machine learning and deep learning based approach. *Appl. Comput. Geosci.* 23, 100173. https://doi.org/10.1016/j.acags.2024.100173.

Saraiva, S., Markus Meier, H.E., Andersson, H., Höglund, A., Dieterich, C., Gröger, M., Hordoir, R., Eilola, K., 2019a. Baltic Sea ecosystem response to various nutrient load scenarios in present and future climates. *Clim. Dyn.* 52, 3369–3387. https://doi.org/10.1007/s00382-018-4330-0.

Saraiva, S., Meier, H.E.M., Andersson, H., Höglund, A., Dieterich, C., Gröger, M., Hordoir, R., Eilola, K., 2019b. Uncertainties in projections of the Baltic sea ecosystem driven by an ensemble of global climate models. *Front. Earth Sci.* 6. https://doi.org/10.3389/feart.2018.00244.

Sayre, R., Butler, K., Van Graafeiland, K., Breyer, S., Wright, D., Frye, C., Karagulle, D., Martin, M., Cress, J., Allen, T., Allee, R.J., Parsons, R., Nyberg, B., Costello, M.J., Harris, P., Muller-Karger, F.E., 2021. A global ecological classification of coastal segment units to complement marine biodiversity observation network assessments. Oceanography 34.

Schrum, C., Hubner, U., Jacob, D., Podzun, R., 2003. A coupled atmosphere/ice/ocean model for the North Sea and the Baltic Sea. *Clim. Dyn.* 21, 131–151. https://doi.org/10.1007/s00382-003-0322-8.

Schuttelaars, H.M., de Jonge, V.N., Chernetsky, A., 2013. Improving the predictive power when modelling physical effects of human interventions in estuarine systems. *Ocean Coast. Manag.* 79, 70–82. https://doi.org/10.1016/j.ocecoaman.2012.05.009.

Schwalm, C.R., Glendon, S., Duffy, P.B., 2020. RCP8.5 tracks cumulative CO<sub>2</ sub> emissions. *Proc. Natl. Acad. Sci.* 117, 19656–19657. https://doi.org/10.1073/pnas.2007117117.

Séférian, R., Berthet, S., Yool, A., Palmiéri, J., Bopp, L., Tagliabue, A., Kwiatkowski, L., Aumont, O., Christian, J., Dunne, J., Gehlen, M., Ilyina, T., John, J.G., Li, H., Long, M.C., Luo, J.Y., Nakano, H., Romanou, A., Schwinger, J., Stock, C., Santana-Falcón, Y., Takano, Y., Tjiputra, J., Tsujino, H., Watanabe, M., Wu, T., Wu, F., Yamamoto, A., 2020. Tracking improvement in simulated marine biogeochemistry between CMIP5 and CMIP6. *Curr. Clim. Change Rep.* 6, 95–119. https://doi.org/10.1007/s40641-020-00160-0.

Sein, D.V., Martyanov, S.D., Dvornikov, A.Y., Cabos, W., Ryabchenko, V.A., Mishra, A.K., Limareva, N., Alekseeva, E., Jacob, D., Kumar, P., 2024. Future climate change in the Northern Indian Ocean as simulated with a high-resolution regional earth system model. *Clim. Dyn.* 62, 911–932. https://doi.org/10.1007/s00382-023-06939-9.

Semmler, T., Danilov, S., Gierz, P., Goessling, H.F., Hegewald, J., Hinrichs, C., Koldunov, N., Khosravi, N., Mu, L., Rackow, T., Sein, D.V., Sidorenko, D., Wang, Q., Jung, T., 2020. Simulations for CMIP6 with the AWI climate model AWI-CM-1-1. *J. Adv. Model. Earth Syst.* 12, e2019MS002009. https://doi.org/10.1029/2019MS002009.

Senatore, A., Furnari, L., Mendicino, G., 2020. Impact of high-resolution sea surface temperature representation on the forecast of small Mediterranean catchments' hydrological responses to heavy precipitation. *Hydrol. Earth Syst. Sci.* 24, 269–291. https://doi.org/10.5194/hess-24-269-2020.

Seneviratne, S.I., Zhang, X., Adnan, M., Badi, W., Dereczynski, C., Di Luca, A., Ghosh, S., Iskandar, I., Kossin, J., Lewis, S., Otto, F., Pinto, I., Satoh, M., Vicente-Serrano, S.M., Wehner, M., Zhou, B., 2023. Weather and climate extreme events in a changing climate. In: Intergovernmental Panel on Climate, C. (Ed.), Climate Change 2021 – The Physical Science Basis: Working Group I Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, pp. 1513–1766. https://doi.org/10.1017/9781009157896.013.

Serafin, K.A., Ruggiero, P., Stockdon, H.F., 2017. The relative contribution of waves, tides, and nontidal residuals to extreme total water levels on U.S. West Coast sandy beaches. *Geophys. Res. Lett.* 44, 1839–1847. https://doi.org/10.1002/2016GL071020.

Sexton, D.M.H., McSweeney, C.F., Rostron, J.W., Yamazaki, K., Booth, B.B.B., Murphy, J. M., Regayre, L., Johnson, J.S., Karmalkar, A.V., 2021. A perturbed parameter ensemble of HadGEM3-GC3.05 coupled model projections: part 1: selecting the parameter combinations. *Clim. Dyn.* 56, 3395–3436. https://doi.org/10.1007/s00382-021-05709-9.

Shears, N.T., Bowen, M.M., 2017. Half a century of coastal temperature records reveal complex warming trends in western boundary currents. *Sci. Rep.* 7, 14527. https://doi.org/10.1038/s41598-017-14944-2.

Shen, C., Appling, A.P., Gentine, P., Bandai, T., Gupta, H., Tartakovsky, A., Baity-Jesi, M., Fenicia, F., Kifer, D., Li, L., Liu, X., Ren, W., Zheng, Y., Harman, C.J., Clark, M., Farthing, M., Feng, D., Kumar, P., Aboelyazeed, D., Rahmani, F., Song, Y., Beck, H.E., Bindas, T., Dwivedi, D., Fang, K., Höge, M., Rackauckas, C., Mohanty, B., Roy, T., Xu, C., Lawson, K., 2023. Differentiable modelling to unify machine learning and physical models for geosciences. *Nat. Rev. Earth Environ.* 4, 552–567. https://doi.org/10.1038/s43017-023-00450-9.

Shepherd, T.G., Boyd, E., Calel, R.A., Chapman, S.C., Dessai, S., Dima-West, I.M., Fowler, H.J., James, R., Maraun, D., Martius, O., Senior, C.A., Sobel, A.H., Stainforth, D.A., Tett, S.F.B., Trenberth, K.E., van den Hurk, B.J.J.M., Watkins, N.W., Wilby, R.L., Zenghelis, D.A., 2018. Storylines: an alternative approach to representing uncertainty in physical aspects of climate change. *Clim. Change* 151, 555–571. https://doi.org/10.1007/s10584-018-2317-9.

Shevchenko, I., Berloff, P., 2023. A hyper-parameterization method for comprehensive ocean models: advection of the image point. *Ocean Model.* 184, 102208. https://doi.org/10.1016/j.ocemod.2023.102208.

Siedlecki, S., Salisbury, J., Gledhill, D., Bastidas, C., Meseck, S., McGarry, K., Hunt, C., Alexander, M., Lavoie, D., Wang, Z., Scott, J., Brady, D., Mlsna, I., Azetsu-Scott, K., Liberti, C., Melrose, D., White, M., Pershing, A., Vandemark, D., Townsend, D., Chen, C., Mook, W., Morrison, R., 2021. Projecting ocean acidification impacts for the Gulf of Maine to 2050: New tools and expectations. *Elementa: Sci. Anthropocene* 9. Doi: 10.1525/elementa.2020.00062.

Siegel, D.A., Buesseler, K.O., Doney, S.C., Sailley, S.F., Behrenfeld, M.J., Boyd, P.W., 2014. Global assessment of ocean carbon export by combining satellite observations and food-web models. *Global Biogeochem. Cycles* 28, 181–196. https://doi.org/10.1002/2013GB004743.

Smale, D.A., Wernberg, T., Oliver, E.C.J., Thomsen, M., Harvey, B.P., Straub, S.C., Burrows, M.T., Alexander, L.V., Benthuysen, J.A., Donat, M.G., Feng, M., Hobday, A.J., Holbrook, N.J., Perkins-Kirkpatrick, S.E., Scannell, H.A., Sen Gupta, A., Payne, B.L., Moore, P.J., 2019. Marine heatwaves threaten global biodiversity and the provision of ecosystem services. *Nat. Clim. Chang.* 9, 306–312. https://doi.org/10.1038/s41558-019-0412-1.

Smith, J.A., Pozo Buil, M., Muhling, B., Tommasi, D., Brodie, S., Frawley, T.H., Fiechter, J., Koenigstein, S., Himes-Cornell, A., Alexander, M.A., Bograd, S.J., Cordero Quirós, N., Crowder, L.B., Curchitser, E., Green, S.J., Hardy, N.A., Haynie, A.C., Hazen, E.L., Holsman, K., Le Fol, G., Lezama-Ochoa, N., Rykaczewski, R.R., Stock, C.A., Stohs, S., Sweeney, J., Welch, H., Jacox, M.G., 2023. Projecting climate change impacts from physics to fisheries: a view from three California Current fisheries. *Prog. Oceanogr.* 211, 102973. https://doi.org/10.1016/j.pocean.2023.102973.

Solan, M., Spencer, T., Paterson, D.M., Unsworth, C.A., Christie, E.K., Blight, A.J., Brown, J., Brooks, H., Lichtman, I.D., Wei, X., Li, X., Thorne, P., Leyland, J., Godbold, J.A., Thompson, C., Williams, M.E., Plater, A., Moller, I., Amoudry, L.O., 2023. Biological–physical interactions are fundamental to understanding and managing coastal dynamics. *R. Soc. Open Sci.* 10, 230155. https://doi.org/10.1098/rsos.230155.

Somot, S., Coppola, E., Solmon, F., Jordà, G., Sannino, G., Ahrens, B., Sevault, F., Reale, M., 2024. Med-CORDEX phase 3: Common protocol for the Baseline runs for the CORDEX-CMIP6 framework (Version v20240614). Zenodo. https://doi.org/10.5281/zenodo.11659642.

Somot, S., Sevault, F., Déqué, M., Crépon, M., 2008. 21st century climate change scenario for the Mediterranean using a coupled atmosphere-ocean regional climate model. *Global Planet. Change* 63, 112–126. https://doi.org/10.1016/j.gloplacha.2007.10.003.

Sonnewald, M., Dutkiewicz, S., Hill, C., Forget, G., 2020. Elucidating ecological complexity: Unsupervised learning determines global marine eco-provinces. *Sci. Adv.* 6, eaay4740. https://doi.org/10.1126/sciadv.aay4740.

Soontiens, N., Allen, S.E., 2017. Modelling sensitivities to mixing and advection in a sill-basin estuarine system. *Ocean Model.* 112, 17–32. https://doi.org/10.1016/j.ocemod.2017.02.008.

Sotillo, M.G., Drevillon, M., Hernandez, F., In Review, 2024. A description of Validation Processes and Techniques for Ocean Forecasting. *State Planet Discuss*, [Prerint]. DOI: 10.5194/sp-2024-33.

Stadnyk, T.A., Tefs, A., Broesky, M., Déry, S.J., Myers, P.G., Ridenour, N.A., Koenig, K., Vonderbank, L., Gustafsson, D., 2021. Changing freshwater contributions to the Arctic: A 90-year trend analysis (1981–2070). *Elementa: Science of the Anthropocene*, 9. 10.1525/elementa.2020.00098.

Staneva, J., Alari, V., Breivik, O., Bidlot, J.R., Mogensen, K., 2017. Effects of wave-induced forcing on a circulation model of the North Sea. *Ocean Dyn.* 67, 81–101. https://doi.org/10.1007/s10236-016-1009-0.

Storkey, D., Blaker, A.T., Mathiot, P., Megann, A., Aksenov, Y., Blockley, E.W., Calvert, D., Graham, T., Hewitt, H.T., Hyder, P., Kuhlbrodt, T., Rae, J.G.L., Sinha, B., 2018. UK Global Ocean GO6 and GO7: a traceable hierarchy of model resolutions. *Geosci. Model Dev.* 11, 3187–3213. https://doi.org/10.5194/gmd-11-3187-2018.

Straneo, F., Heimbach, P., 2013. North Atlantic warming and the retreat of Greenland's outlet glaciers. *Nature* 504, 36–43. https://doi.org/10.1038/nature12854.

Sun, Q., Whitney, M.M., Bryan, F.O., Tseng, Y.-H., 2017. A box model for representing estuarine physical processes in Earth system models. *Ocean Model.* 112, 139–153. https://doi.org/10.1016/j.ocemod.2017.03.004.

Tinker, J., Palmer, M.D., Harrison, B.J., O'Dea, E., Sexton, D.M.H., Yamazaki, K., Rostron, J.W., 2024. Twenty-first century marine climate projections for the NW European shelf seas based on a perturbed parameter ensemble. *Ocean Sci.*, 20, 835–885. https://doi.org/10.5194/os-20-835-2024.

Tittensor, D.P., Eddy, T.D., Lotze, H.K., Galbraith, E.D., Cheung, W., Barange, M., Blanchard, J.L., Bopp, L., Bryndum-Buchholz, A., Büchner, M., Bulman, C., Carozza, D.A., Christensen, V., Coll, M., Dunne, J.P., Fernandes, J.A., Fulton, E.A., Hobday, A.J., Huber, V., Jennings, S., Jones, M., Lehodey, P., Link, J.S., Mackinson, S., Maury, O., Niiranen, S., Oliveros-Ramos, R., Roy, T., Schewe, J., Shin, Y.J., Silva, T., Stock, C.A., Steenbeek, J., Underwood, P.J., Volkholz, J., Watson, J.R., Walker, N.D., 2018. A protocol for the intercomparison of marine fishery and ecosystem models: Fish-MIP v1.0. *Geosci. Model Dev.*, 11, 1421–1442. https://doi.org/10.5194/gmd-11-1421-2018.

Toimil, A., Camus, P., Losada, I.J., Le Cozannet, G., Nicholls, R.J., Idier, D., Maspataud, A., 2020. Climate change-driven coastal erosion modelling in temperate sandy beaches: Methods and uncertainty treatment. *Earth Sci. Rev.* 202, 103110. https://doi.org/10.1016/j.earscirev.2020.103110.

Trotta, F., Federico, I., Pinardi, N., Coppini, G., Causio, S., Jansen, E., Iovino, D., Masina, S., 2021. A Relocatable Ocean Modeling Platform for Downscaling to Shelf-Coastal Areas to Support Disaster Risk Reduction. *Front. Mar. Sci.* 8. https://doi.org/10.3389/fmars.2021.642815.

Uchida, T., Le Sommer, J., Stern, C., Abernathey, R.P., Holdgraf, C., Albert, A., Brodeau, L., Chassignet, E.P., Xu, X., Gula, J., Roullet, G., Koldunov, N., Danilov, S., Wang, Q., Menemenlis, D., Bricaud, C., Arbic, B.K., Shriver, J.F., Qiao, F., Xiao, B., Biastoch, A., Schubert, R., Fox-Kemper, B., Dewar, W.K., Wallcraft, A., 2022. Cloud-based framework for inter-comparing submesoscale-permitting realistic ocean models. *Geosci. Model Dev.* 15, 5829–5856. https://doi.org/10.5194/gmd-15-5829-2022.

van de Wal, R., Melet, A., Bellafiore, D., Camus, P., Ferrarin, C., Oude Essink, G., Haigh, I.D., Lionello, P., Luijendijk, A., Toimil, A., Staneva, J., Vousdoukas, M., 2024. Sea Level Rise in Europe: Impacts and consequences. *Sea Level Rise in Europe: 1st Assessment Report of the Knowledge Hub on Sea Level Rise (SLRE1)*, 3-slre1, 5. 10.5194/sp-3-slre1-5-2024.

van den Hurk, B., Pinardi, N., Kiefer, T., Larkin, K., Manderscheid, P., Richter, K., (Eds.), 2024. *Sea Level Rise in Europe: 1st Assessment Report of the Knowledge Hub on Sea Level Rise (SLRE1)*: Copernicus Publications. 10.5194/sp-3-slre1.

van Hooidonk, R., Maynard, J., Tamelander, J., Gove, J., Ahmadia, G., Raymundo, L., Williams, G., Heron, S.F., Planes, S., 2016. Local-scale projections of coral reef futures and implications of the Paris Agreement. *Sci. Rep.* 6, 39666. https://doi.org/10.1038/srep39666.

van Vloten, S.O., Cagigal, L., Rueda, A., Ripoll, N., Méndez, F.J., 2022. HyTCWaves: a hybrid model for downscaling tropical cyclone induced extreme Waves climate. *Ocean Model.* 178, 102100. https://doi.org/10.1016/j.ocemod.2022.102100.

Verri, G., Furnari, L., Gunduz, M., Senatore, A., Santos da Costa, V., De Lorenzis, A., Fedele, G., Manco, I., Mentaschi, L., Clementi, E., Coppini, G., Mercogliano, P., Mendicino, G., Pinardi, N., 2024. Climate projections of the Adriatic Sea: role of river release. *Front. Clim.* 6. https://doi.org/10.3389/fclim.2024.1368413.

Verri, G., Pinardi, N., Bryan, F., Tseng, Y.-H., Coppini, G., Clementi, E., 2020. A box model to represent estuarine dynamics in mesoscale resolution ocean models. *Ocean Model.* 148, 101587. https://doi.org/10.1016/j.ocemod.2020.101587.

Vitousek, S., Barnard, P.L., Limber, P., Erikson, L., Cole, B., 2017. A model integrating longshore and cross-shore processes for predicting long-term shoreline response to climate change. *J. Geophys. Res. Earth* 122, 782–806. https://doi.org/10.1002/2016JF004065.

Vousdoukas, M.I., Mentaschi, L., Voukouvalas, E., Verlaan, M., Jevrejeva, S., Jackson, L.P., Feyen, L., 2018. Global probabilistic projections of extreme sea levels show intensification of coastal flood hazard. *Nat. Commun.* 9, 2360. https://doi.org/10.1038/s41467-018-04692-w.

Wåhlström, I., Almroth-Rosell, E., Edman, M., Olofsson, M., Eilola, K., Fleming, V., Gröger, M., Arneborg, L., Meier, H.E.M., 2024. Increased nutrient retention and cyanobacterial blooms in a future coastal zone. *Estuar. Coast. Shelf Sci.* 301, 108728. https://doi.org/10.1016/j.ecss.2024.108728.

Wakelin, S.L., Artioli, Y., Holt, J.T., Butenschön, M., Blackford, J., 2020. Controls on near-bed oxygen concentration on the Northwest European Continental Shelf under a potential future climate scenario. *Prog. Oceanogr.* 102400. https://doi.org/10.1016/j.pocean.2020.102400.

Wang, P., Bernier, N.B., Thompson, K.R., 2022. Adding baroclinicity to a global operational model for forecasting total water level: Approach and impact. *Ocean Model.* 174, 102031. https://doi.org/10.1016/j.ocemod.2022.102031.

Wang, Q., Ilicak, M., Gerdes, R., Drange, H., Aksenov, Y., Bailey, D.A., Bentsen, M., Biastoch, A., Bozec, A., Böning, C., Cassou, C., Chassignet, E., Coward, A.C., Curry, B., Danabasoglu, G., Danilov, S., Fernandez, E., Fogli, P.G., Fujii, Y., Griffies, S.M., Iovino, D., Jahn, A., Jung, T., Large, W.G., Lee, C., Lique, C., Lu, J., Masina, S., Nurser, A.J.G., Rabe, B., Roth, C., Salas y Mélia, D., Samuels, B.L., Spence, P., Tsujino, H., Valcke, S., Voldoire, A., Wang, X., Yeager, S.G., 2016a. An assessment of the Arctic Ocean in a suite of interannual CORE-II simulations. Part I: Sea ice and solid freshwater. *Ocean Model.* 99, 110–132. https://doi.org/10.1016/j.ocemod.2015.12.008.

Wang, Q., Ilicak, M., Gerdes, R., Drange, H., Aksenov, Y., Bailey, D.A., Bentsen, M., Biastoch, A., Bozec, A., Böning, C., Cassou, C., Chassignet, E., Coward, A.C., Curry, B., Danabasoglu, G., Danilov, S., Fernandez, E., Fogli, P.G., Fujii, Y., Griffies, S.M., Iovino, D., Jahn, A., Jung, T., Large, W.G., Lee, C., Lique, C., Lu, J., Masina, S., Nurser, A.J.G., Rabe, B., Roth, C., Salas y Mélia, D., Samuels, B.L., Spence, P., Tsujino, H., Valcke, S., Voldoire, A., Wang, X., Yeager, S.G., 2016b. An assessment of the Arctic Ocean in a suite of interannual CORE-II simulations. Part II: liquid freshwater. *Ocean Modelling* 99, 86–109. https://doi.org/10.1016/j.ocemod.2015.12.009.

Wang, Q., Koldunov, N.V., Danilov, S., Sidorenko, D., Wekerle, C., Scholz, P., Bashmachnikov, I.L., Jung, T., 2020. Eddy kinetic energy in the arctic ocean from a global simulation with a 1-km arctic. *Geophys. Res. Lett.* 47, e2020GL088550. https://doi.org/10.1029/2020GL088550.

Ward, B.A., Follows, M.J., 2016. Marine mixotrophy increases trophic transfer efficiency, mean organism size, and vertical carbon flux. *Proc. Natl. Acad. Sci.* 113, 2958–2963. https://doi.org/10.1073/pnas.1517118113.

Ward, N.D., Megonigal, J.P., Bond-Lamberty, B., Bailey, V.L., Butman, D., Canuel, E.A., Diefenderfer, H., Ganju, N.K., Goñi, M.A., Graham, E.B., Hopkinson, C.S., Khangaonkar, T., Langley, J.A., McDowell, N.G., Myers-Pigg, A.N., Neumann, R.B., Osburn, C.L., Price, R.M., Rowland, J., Sengupta, A., Simard, M., Thornton, P.E., Tzortziou, M., Vargas, R., Weisenhorn, P.B., Windham-Myers, L., 2020. Representing the function and sensitivity of coastal interfaces in Earth system models. *Nat. Commun.* 11, 2458. https://doi.org/10.1038/s41467-020-16236-2.

Wassmann, P., Kosobokova, K.N., Slagstad, D., Drinkwater, K.F., Hopcroft, R.R., Moore, S.E., Ellingsen, I., Nelson, R.J., Carmack, E., Popova, E., Berge, J., 2015. The contiguous domains of Arctic Ocean advection: Trails of life and death. *Prog. Oceanogr.* 139, 42–65. https://doi.org/10.1016/j.pocean.2015.06.011.

Wei, X., Williams, M.E., Brown, J.M., Thorne, P.D., Amoudry, L.O., 2022. Salt Intrusion as a Function of Estuary Length in Periodically Weakly Stratified Estuaries. *Geophys. Res. Lett.* 49, e2022GL099082. https://doi.org/10.1029/2022GL099082.

Woodworth, P.L., Melet, A., Marcos, M., Ray, R.D., Wöppelmann, G., Sasaki, Y.N., Cirano, M., Hibbert, A., Huthnance, J.M., Monserrat, S., Merrifield, M.A., 2019. Forcing factors affecting sea level changes at the coast. *Surv. Geophys.* 40, 1351–1397. https://doi.org/10.1007/s10712-019-09531-1.

Wu, L.X., Cai, W.J., Zhang, L.P., Nakamura, H., Timmermann, A., Joyce, T., McPhaden, M.J., Alexander, M., Qiu, B., Visbecks, M., Chang, P., Giese, B., 2012. Enhanced warming over the global subtropical western boundary currents. *Nat. Clim. Chang.* 2, 161–166. https://doi.org/10.1038/nclimate1353.

Xu, Z., Han, Y., Tam, C.-Y., Yang, Z.-L., Fu, C., 2021. Bias-corrected CMIP6 global dataset for dynamical downscaling of the historical and future climate (1979–2100). *Sci. Data* 8, 293. https://doi.org/10.1038/s41597-021-01079-3.

Yang, H., Lohmann, G., Wei, W., Dima, M., Ionita, M., Liu, J., 2016. Intensification and poleward shift of subtropical western boundary currents in a warming climate. *J. Geophys. Res. Oceans* 121, 4928–4945. https://doi.org/10.1002/2015JC011513.

Yool, A., Palmiéri, J., Jones, C.G., Sellar, A.A., de Mora, L., Kuhlbrodt, T., Popova, E.E., Mulcahy, J.P., Wiltshire, A., Rumbold, S.T., Stringer, M., Hill, R.S.R., Tang, Y., Walton, J., Blaker, A., Nurser, A.J.G., Coward, A.C., Hirschi, J., Woodward, S., Kelley, D.I., Ellis, R., Rumbold-Jones, S., 2020. Spin-up of UK earth system model 1 (UKESM1) for CMIP6. *J. Adv. Model. Earth Syst.* 12, e2019MS001933. https://doi.org/10.1029/2019MS001933.

Zanna, L., Bolton, T., 2020. Data-driven equation discovery of ocean mesoscale closures. *Geophys. Res. Lett.* 47, e2020GL088376. https://doi.org/10.1029/2020GL088376.

Zhao, N., Nasuno, T., 2020. How does the air-sea coupling frequency affect convection during the MJO passage? *J. Adv. Model. Earth Syst.* 12, e2020MS002058. https://doi.org/10.1029/2020MS002058.