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Quo Vadimus

Next-generation regional ocean projections for living marine resource management in a changing climate

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Efforts to manage living marine resources (LMRs) under climate change need projections of future ocean conditions, yet most global climate models (GCMs) poorly represent critical coastal habitats. GCM utility for LMR applications will increase with higher spatial resolution but obstacles including computational and data storage costs, obstinate regional biases, and formulations prioritizing global robustness over regional skill will persist. Downscaling can help address GCM limitations, but significant improvements are needed to robustly support LMR science and management. We synthesize past ocean downscaling efforts to suggest a protocol to achieve this goal. The protocol emphasizes LMR-driven design to ensure delivery of decision-relevant information. It prioritizes ensembles of downscaled projections spanning the range of ocean futures with durations long enough to capture climate change signals. This demands judicious resolution refinement, with pragmatic consideration for LMR-essential ocean features superseding theoretical investigation. Statistical downscaling can complement dynamical approaches in building these ensembles. Inconsistent use of bias correction indicates a need for objective best practices. Application of the suggested protocol should yield regional ocean projections that, with effective dissemination and translation to decision-relevant analytics, can robustly support LMR science and management under climate change.

Keywords: climate change, downscaling, fisheries, living marine resources, marine ecosystems, protected marine species

Introduction

Climate change poses an unprecedented challenge for living marine resource (LMR) managers and stakeholders: rising temperatures, changing ocean circulation, alterations to ocean chemistry, and potential shifts in ocean productivity baselines will all affect the suitability of critical LMR habitats and their capacity to support productive fisheries and vibrant coastal economies (Bindoff *et al.*, 2019). Risks extend to public health through shifts in the occurrence and severity of marine pathogens (Burge *et al.*, 2014; Muhling *et al.*, 2017) and harmful algal blooms (Wells *et al.*, 2020) in conjunction with increasing coastal aquaculture. The potential for numerous stakeholders to be affected by environmentally driven changes in local LMRs warrants incorporating climate change considerations in LMR science, policy, scenario planning, and management strategy development (Free *et al.*, 2020). For example, Gaines *et al.* (2018) project a 25% decline in maximum sustainable yield of global fisheries under a business-as-usual emissions scenario [Relative Concentration Pathway (RCP) 8.5] by 2100 due to climate change. However, implementing adaptive management measures that account for changes in both stock productivity and distribution can mitigate reductions in global fishery biomass, harvest, and overall profits (Gaines *et al.*, 2018; Free *et al.*, 2020; Holsman *et al.*, 2020).

Projections of the range of potential ocean and LMR futures under different climate and management scenarios are critical for formulating effective LMR-management strategies (e.g. Link *et al.*, 2015). However, most LMR management operates at regional scales, often within a country's Exclusive Economic Zone (EEZ), which extends 200 nautical miles (370 km) offshore. Application of global climate model (GCM) projections contributed to the sixth Coupled Model Intercomparison Project (CMIP6, Eyring *et al.*, 2016) in regional contexts is limited by coarse ocean resolution, often 0.5°–1° (∼50–100 km) in the horizontal (Kwiatkowski *et al.*, 2020; Séférian *et al.*, 2020). Many EEZs include shallow (depth < 200 m) continental shelf environments with complex bathymetry, circulation, and physical-biological dynamics that are not resolved at these resolutions (Holt *et al.*, 2017), contributing to pronounced GCM biases at regional scales (Stock *et al.*, 2011). These issues are compounded by GCM emphasis on globally robust, rather than regionally optimal, formulations, data storage limitations, and the often large spread in projected regional climate and ocean trends relative to global mean tendencies (Deser *et al.*, 2012a, b; Bindoff *et al.*, 2013; Frolicher *et al.*, 2016).

The growing demand for improved climate change projections at sub-continental to local scales spans disparate sectors such as agriculture (e.g. Fischer *et al.*, 2002), water resources (e.g. Rayner *et al.*, 2005), urban planning (e.g. Smid and Costa, 2018), air quality (e.g. Cai *et al.*, 2017), and food security (e.g. Parry *et al.*, 2004; Rice and Garcia, 2011). Filling this demand has thus been identified as a cornerstone in addressing the grand scientific challenges set forth by the World Climate Research Programme (Eyring *et al.*, 2016). It has furthermore motivated numerous regional climate change downscaling projects, defined as the inferring of small-scale features from large-scale information using dynamical or statistical methods (e.g. Giorgi and Mearns, 1991). Such efforts include concerted international programs such as the Coordinated Regional Climate Downscaling Experiment (CORDEX, Giorgi *et al.*, 2009). However, with few exceptions (e.g. Med-CORDEX, Ruti *et al.*, 2016), these large-scale, coordinated undertakings have been predominantly atmosphere-focused with linkages to terrestrial applications [e.g. agriculture and water resource management (Fowler *et al.*, 2007; Chen *et al.*, 2013)], rather than focusing on marine environments. Numerous regional ocean-modelling studies have independently, or within limited consortia, developed downscaled ocean projections (Table S1). These have supported diverse studies of climate change impacts on LMRs, yet core aspects of the downscaling approach have varied across efforts. There is a need for more clearly defined best practices that can support management and be defended in this context. Meanwhile, advances in computation and models have raised the prospect of improved GCM performance at regional scales and coastal environments (e.g. Saba *et al.*, 2016; Liu *et al.*, 2019) and expanded LMR-applications (e.g. Kleisner *et al.*, 2017; Stock *et al.*, 2017). How then should we construct the next generation of regional ocean projections to best support LMR science and management in a changing climate?

This contribution synthesizes literature from the global climate modelling and ocean climate downscaling communities to assess the extent to which current efforts meet, and can better address regional ocean and biogeochemical projection needs for LMR applications. We first contend that further improvements in the regional performance of GCMs are likely to increase their utility for regional marine resource management applications. However, these modelling gains will be hard-won and the significant limitations characteristic of current GCMs are likely to persist (Holt *et al.*, 2017), thus supporting the continued potential for significant contributions from regional ocean downscaling and projections.

Next, we assess the capacity of previous ocean downscaling studies to address GCM limitations for LMR applications. We find that, in many cases, past studies have succeeded in projecting changes in a subset of LMR-critical ocean features and phenomena left unresolved in GCMs. In the most striking cases, skillful resolution of finer scale ocean processes has revealed ocean trends that differ significantly from, and may even be opposite to, those in the coarse resolution driving GCM (Figure 1). Such insights have shaped our understanding of LMR risks under climate change. However, we also find that past downscaling studies often omitted LMR-critical phenomena, inherited biases from GCMs, had methodological inconsistencies, did not effectively assess the range of ocean futures, and had limited capacity to disseminate and intercompare results. These limitations of past downscaling efforts have significantly hindered the integration of climate change information into LMR management strategies. Therefore, we outline a protocol for future efforts to address the limitations of past downscaling efforts for LMR science and management applications. Finally, we recognize that even com-

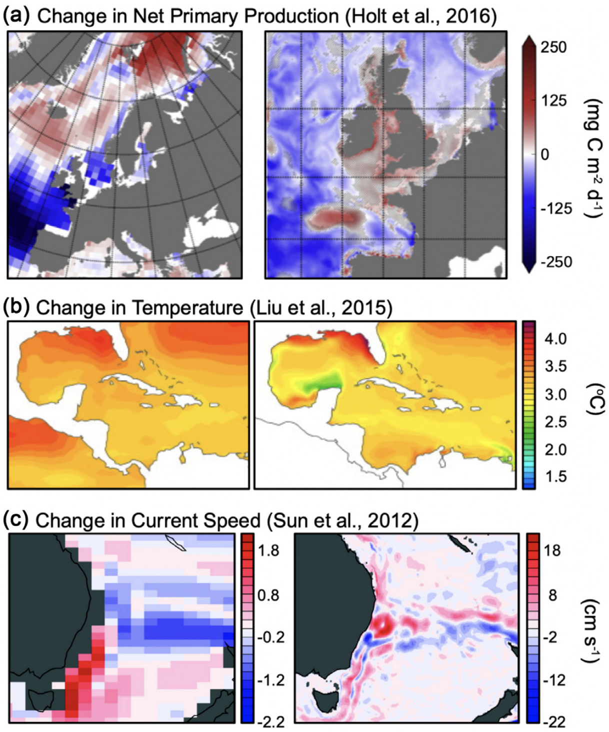

Figure 1. Examples illustrating the potential value added by downscaling climate change impacts on marine environments; each row contrasts the dynamically downscaled model (right-hand panel) with its forcing GCM (left-hand panel): (a) Sign reversal (positive vs. negative) in a change in net primary productivity for the near-shore Northwest European Shelf (Holt *et al.*, 2016). (b) More heterogeneous change in August–September–October sea surface temperature in the Intra-Americas Seas (Liu *et al.*, 2015; reproduced with permission from Elsevier, Journal of Marine Systems). (c) Larger magnitude of change in current speed off the western coast of Australia (Sun *et al.*, 2012 © American Meteorological Society. Used with permission).

prehensive ensembles of projections that span the range of potential future conditions require robust observation, science, and management infrastructure in order to translate them into the actionable information needed for developing LMR management decisions and strategies. We thus conclude with a discusson on the challenges of translating next-generation regional ocean projections into improved management decisions.

Hard-won regional climate fidelity gains for global models

Although GCMs have improved considerably over the past several decades (Flato *et al.*, 2013), significant regional biases persist, and GCMs continue to be most reliable at basin-to-global scales (Grotch and MacCracken, 1991; Flato *et al.*, 2013; Fox-Kemper *et al.*, 2019). Furthermore, there are several reasons why it is unlikely that anticipated advances in GCM formulations and configurations will fully address resolution, bias, model configuration, and output storage issues that currently hinder the application of GCMs to LMR science and management challenges in the near future.

First, the refined resolution is a key element for improving GCM performance at regional scales (Fox-Kemper *et al.*, 2019). However, higher resolution globally is cumbersome, as an n-fold increase in horizontal resolution is generally accompanied by at least an n^3 increase in computational cost: a factor of n for each horizontal dimension and for the shorter time-step required for numerical stability. Therefore, refining GCMs that are presently configured for $\sim$1° Lat/Lon, to resolutions typical of coastal ocean models ($\sim$10 km, Table S1) would incur at least a 1000-fold increase in computational cost (NRC, 2012). This cost would be further exacerbated by desired improvements in vertical and process resolution (e.g. explicit tidal currents) to better capture coastal dynamics (Holt *et al.*, 2017).

Global simulations at $\sim$10 km have been conducted (e.g. Delworth *et al.*, 2012; Small *et al.*, 2014; Iovino *et al.*, 2016; Turi *et al.*, 2018) and, in a few cases, have been run for the multiple centuries for climate change assessment. These higher resolution simulations often exhibit improved representation of important ocean features and ocean–atmosphere interactions (e.g. Figure S1; Small *et al.*, 2014; Haarsma *et al.*, 2016; Saba *et al.*, 2016). However, globally coordinated experiments associated with the High Resolution Model Intercomparison Project (HighResMIP, Haarsma *et al.*, 2016) primarily targeted atmospheric resolution. When ocean components were included, the horizontal resolution was generally only of the order of 1/4°. Nonetheless, current computational resources still prevented HighResMIP configurations from running the broad set of future emissions scenarios enlisted for climate impacts studies (e.g. ScenarioMIP, O'Neill *et al.*, 2016), or including ocean biogeochemistry and other LMR-relevant earth system components. Under present growth rates in computational power, Holt *et al.* (2017) estimate that it will be at least 10–20 years before fully coupled GCMs used for climate change simulations routinely resolve scales of the order of 1.5 km common in current coastal simulations, while Fox-Kemper *et al.* (2014) project that these models will not be submesoscale resolving (i.e. <0.1 km) before 2060.

Second, retaining and serving output fields for high-resolution GCMs are also costly, necessitating parsimony even at horizontal ocean resolutions of recent CMIP experiments: in the CMIP data hierarchy, Tier 1 (i.e. highest priority) compliance for three-dimensional ocean variables requires monthly output for physical variables (e.g. temperature, salinity, velocity) but only annual output for biogeochemical fields (e.g. dissolved oxygen, inorganic carbon, nitrate). All outputs are mapped onto standard 1° grids. As a result, crucial ecosystem metrics may not be broadly available at the depths or frequencies needed for specific LMR and ecosystem assessments.

Third, regional GCM biases arise not only as a result of the coarse resolution, but also because only broad-scale climate forcings (e.g. greenhouse gases, radiation at the top of the atmosphere, volcanoes) are prescribed for climate change projections (Flato *et al.*, 2013). GCMs used for climate change projections are thus allowed to evolve relatively freely, within the bounds of the planet's physical parameters. This contrasts sharply with, for example, regional retrospective ocean simulations that benefit from, and are constrained by, robust observation-derived estimates of atmospheric and ocean conditions that are applied at the air-sea interface and along the ocean domain boundaries, respectively. That realistic large-scale climate dynamics emerge in GCMs despite the limited nature of externally imposed climate forcing reflects decades of development (Le Treut *et al.*, 2007) and is essential for the holistic study and projection of a dynamically evolving climate system. However, the relatively unconstrained nature of climate change projections also means that even subtle GCM deficiencies are left

Table 1. Terminology; boldface indicates higer-order categories.

Term	Definition
Bias Correction	Techniques used to remove GCM-simulated climate bias in the region of interest. For dynamical ocean downscaling, bias corrections are generally applied to GCM-derived boundary conditions, often through the addition of climatological differences or "deltas." In some climate communities, bias correction strictly refers to a delta addition wherein the climatological difference between observed and modelled historical (i.e. retrospective) conditions is added to the GCM projection prior to downscaling. This method assumes that the bias between GCM and "reality" will not change over time (i.e. stationary assumption) and some biases may not be fully addressed by climatological corrections.
Change Factor	A perturbation of GCM forcing fields, calculated as the difference between modelled future, and historical conditions, which is added to an "observed" historical time-series (e.g. reanalysis product) to create the forcing for the regional climate change simulation. This method is not strictly a "bias correction" but has the effect of removing stationary biases that occur in both modelled future and historical conditions; this technique is often used in time slice experiments.
Dynamical Downscaling	Numerically simulating the effects of large-scale climate processes on regional ocean conditions through a solution of differential equations of state at higher spatial resolution than prescribed by the ocean/climate forcing conditions.
One-way Nested	Solutions generated by the regional ocean model are not communicated to, and thus do not impact the ocean/climate forcing conditions.
Two-way Nested	Solutions generated by the regional ocean model are communicated to the larger, exterior domain, and can impact the broader ocean/climate solution.
Parent Domain	The coarser ocean model that provides boundary and forcing conditions for the nested, higher resolution regional domain.
Child Domain	The interior domain that "inherits" climate and environmental state information from the parent model at its boundaries.
Statistical Downscaling	Extrapolating climate signals to regional scales by applying statistical relationships between contemporaneous GCM-generated climate patterns and regionally observed conditions to GCM output covering unobserved (e.g. future) time periods.
Time Slice Simulation	A simulation of representative climate conditions over a discrete period, typically 10–30 years in duration. For example, an ocean time slice experiment forced by atmospheric conditions from a high carbon emissions scenario over the period 2070–2100 may be compared against a time slice from 1970–2000 to assess the magnitude of century-scale climate-induced ocean changes.
Transient Climate Change Simulation	Multidecadal-to-centennial simulations intended to resolve the time-dependent response of the climate system to accumulating greenhouse gases, aerosols, and other anthropogenic drivers.

unchecked by observation-based constraints, contributing significant biases that would likely be suppressed in configurations that force closer adherence to historical conditions. Thus, while it is possible to reduce GCM biases, they will likely continue to pose significant challenges for regional climate impacts studies.

Fourth, GCMs prioritize global robustness and numerical efficiency over regional optimality. This motivates a variety of decisions regarding model formulations that can compromise the representation of coastal and sub-mesoscale processes. For example, the effects of tides on ocean mixing are generally parameterized by GCMs: while most GCMs augment vertical mixing in response to barotropic tides (Simmons *et al.*, 2004), interior mixing by baroclinic tides and the interaction between tidal boundary layers and stratification are often absent (Luneva *et al.*, 2015), as are net tidal currents and transport of ocean constituents.

Similarly, global ocean biogeochemical models are generally designed for, and assessed against, broad-scale biogeochemical and marine ecosystem variations across ocean biomes (e.g. Séférian *et al.*, 2020) that are most critical for global carbon cycling (not LMRs). As a result, these models often (over)simplify regionally important ecological processes. For example, phytoplankton communities are typically represented by a small number (2–3) of functional types and include limited resolution of plankton food web dynamics often critical for LMRs (Mitra *et al.*, 2014; Laufkotter *et al.*, 2015; Van Oostende *et al.*, 2018). Additionally, GCMs often omit benthic–pelagic interactions critical in many shelf systems but only included in more detailed biogeochemical models applied at regional scales (e.g. Butenschön *et al.*, 2016). While some GCMs specify riverine nutrients based on contemporary global estimates (e.g. Mayorga *et al.*, 2010), many omit them and most have limited representations of biogeochemical transformations on the shelf (e.g. Izett and Fennel, 2018). Efforts are underway to improve biogeochemical model comprehensiveness, but this also imposes a computational cost, and the potential for regional optimization in GCMs will always lag behind region-specific frameworks.

Lastly, as outlined in the introduction, a key requirement of regional ocean projections for LMR applications is simulations spanning potential ocean futures under a range of climate and management scenarios (Link *et al.*, 2015; Hollowed *et al.*, 2020; Holsman *et al.*, 2020). Optimization of models for regional application and subsequent exploration of regional climate/adaptation scenarios requires many simulations. Generating these ensembles, though still expensive, is more practicable with a limited

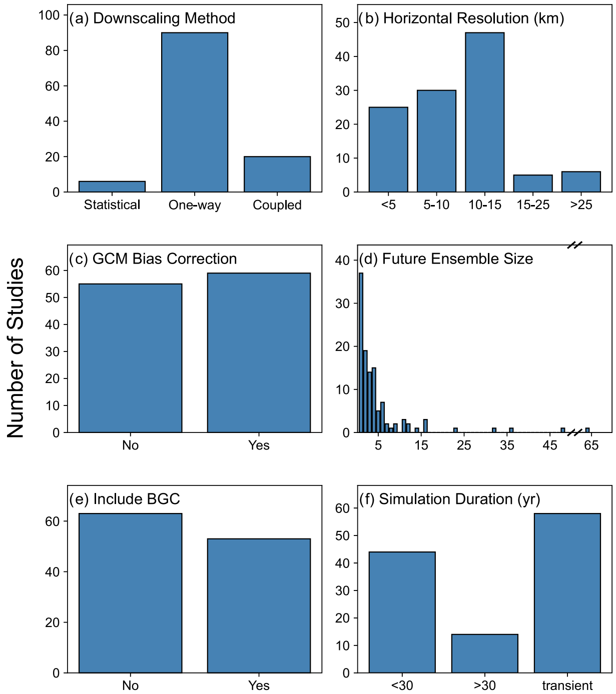

Figure 2. Studies from Table S1 characterized by (a) downscaling method, (b) horizontal grid resolution, (c) whether GCM forcing fields were bias corrected, (d) the number of future simulations generated, (e) whether ocean BGC was included, and (f) the number of years simulated (i.e. time slice length or full transient simulations).

area, rather than a global modelling framework of comparable resolution.

Past regional ocean downscaling efforts

The previous section suggests that while GCMs will improve, they will continue to have significant limitations for regional LMR applications. We now ask whether past regional ocean downscaling efforts effectively addressed GCM limitations. A synthesis of over 100 studies that report on at least one future climate change projection suggests that these efforts provided new insights into regional patterns of ocean change. However, LMR applications with prior downscaling frameworks were often hindered by limited ensemble size, short simulation durations, methodological inconsistencies, limited evaluation against LMR-critical phenomena, and the exclusion of LMR-critical processes.

Following Schrum *et al.* (2016) and Meier *et al.* (2019), who reviewed downscaling efforts for the Northeast Atlantic and European Seas, we have characterized studies based on geographic region, downscaling approach (dynamical vs. statistical; one-way vs. two-way nested, Table 1), horizontal resolution, the number of years simulated, the number of GCMs downscaled, and total future ensemble size, whether GCM forcing fields were bias corrected, and inclusion of a biogeochemistry (BGC) model capable of simulating any subset of plankton productivity, acidification, or oxygen responses (i.e. biogeochemical models of varying levels of complexity were not differentiated).

Consistent with ocean downscaling objectives, the studies summarized in Table S1 offered insights into the response of previously unresolved coastal ocean processes to large-scale climate drivers and/or the effects of previously unresolved factors on large-scale patterns of change. In some cases, the resolution of finerscale responses significantly alters large-scale patterns of change for key ecosystem drivers (Figure 1). These examples illustrate a critical facet of the "added value" for regionally downscaled simulations. While most studies included some level of skill assessment against observations, linkages between such evaluations and LMR-critical phenomena were often included in only a general way. This made success in projecting the range of LMR-critical ocean conditions difficult to gauge.

The majority of previous studies meeting the search criteria dynamically downscaled (Figure 2a) a single or a limited number of projections (often < 3; Figure 2d) using "one-way" nested ocean model configurations (Figure 2a) with horizontal resolutions of ∼5-15 km (Figure 2b). The prevalence of dynamical frameworks indicates (a) recognition of the non-linear and complex ocean processes linking climate forcing to shelf responses (e.g. Holt *et al.*, 2014; Holt *et al.*, 2018); (b) data sparseness relative to terrestrial systems where observation-driven statistical downscaling approaches are more common, (e.g. Ekström *et al.*, 2015); and (c) the availability of numerous regional ocean dynamical modelling systems. The popularity of the "one-way" nesting approach further reflects a predominant interest in the implications of large-scale climate changes on coastal areas and a desire to avoid the need for concurrent, often global simulations required by two-way nesting approaches.

Horizontal resolutions of 5–15 km allow for the representation of many barotropic and baroclinic shelf-sea processes (Holt *et al.*, 2009) and are typical of coastal ocean models intended for long integrations where computational constraints are a prominent consideration. Use of unstructured grids in some cases allowed for further gradations in resolution within the regional domain (e.g. Khangaonkar *et al.*, 2019), but most studies used structured grids. The advantages and disadvantages of these regional modelling frameworks have been discussed in previous synthesis papers (e.g. Fringer *et al.*, 2019).

The small number of projections (Figure 2d) also reflects computational constraints. Many studies, however, also cited a "proof-of-concept" objective and/or the limited scope of exploring the magnitude and nature of projected regional ocean changes as rationale for a single or small number of ensemble members. Meanwhile, studies that downscaled multiple GCMs or considered multiple scenarios often revealed stark contrasts in projected changes with significant LMR management implications (e.g. Figure 3).

Significant methodological inconsistencies were apparent in several areas. Studies were split in their consideration of GCM bias corrections (Figure 2c) and ocean biogeochemistry (Figure 2e), and differed in the duration of simulations (Figure 2f). Approaches also varied among studies that used bias corrections. Most relied on a simple "change-factor" or "delta addition" method to address GCM biases (Table 1). While these methods may seem similar, they actually convey significantly different aspects of the observed and simulated climate signal to the regional model. Furthermore, while most cases considered consistent sets of forcing from GCM-scenario pairs, others (e.g. Dussin *et al.*, 2019) decomposed sets of projected changes into individual perturbations (e.g. warming, shifting winds, altered biogeochemistry along ocean boundaries). Such perturbations offer unique insight into the sensitivities of coastal ecosystems to different elements of climate change forcing, but their looser relationship with a specific dynamically consistent GCM-scenario pair hinders their usage in ensemble projections for management and policy formulation.

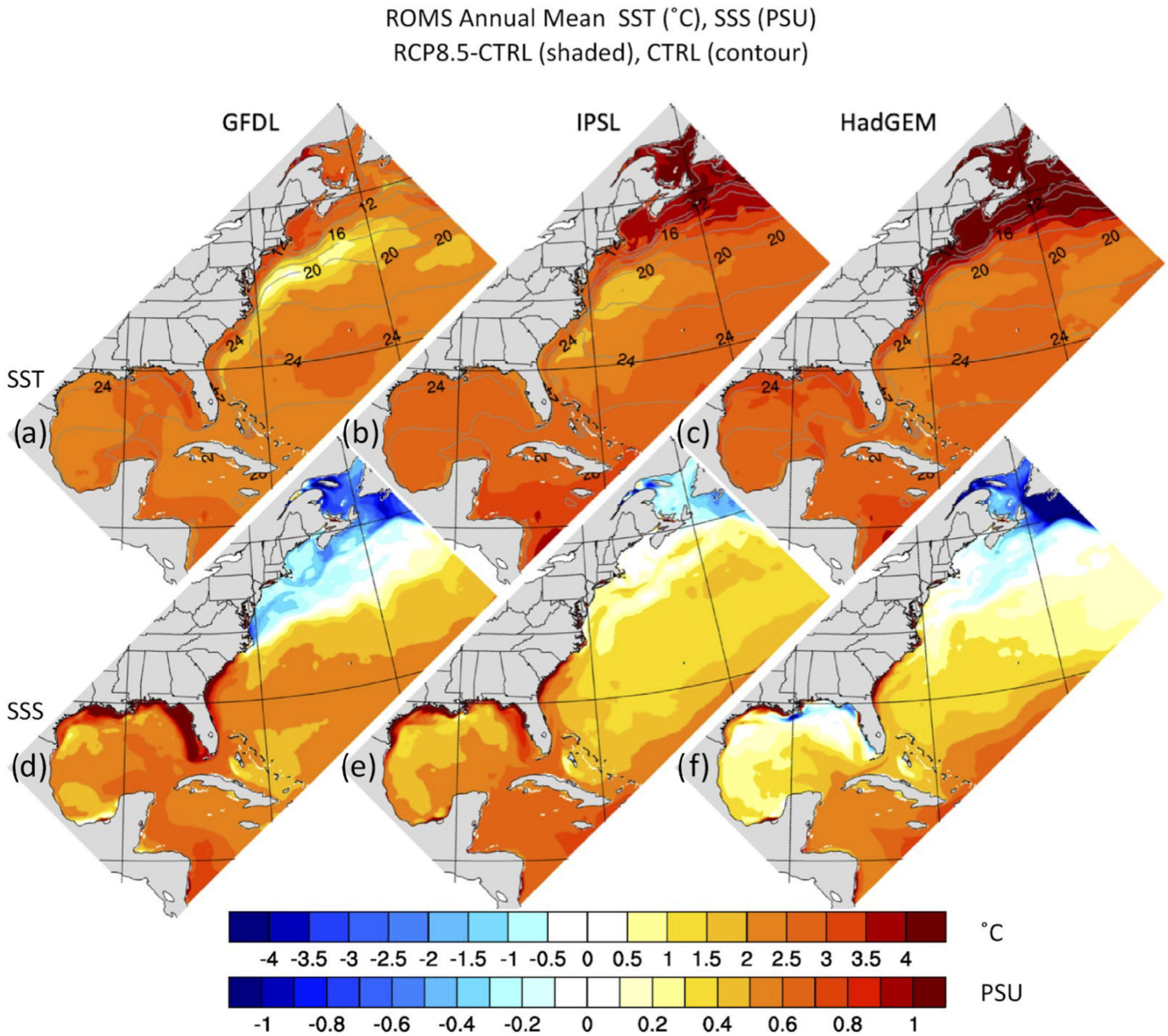

Figure 3. Comparison of downscaled projections of end-of-century changes in annual mean surface temperature (SST °C; top row) and salinity (SSS PSU; bottom row) from three CMIP5 GCMs: GFDL (a, d); IPSL (b, e); HadGEM (c, f). Note the differences in temperature and salinity changes for the different GCMs, underlining the importance of projections spanning the range of ocean futures for climate change applications. Adapted from Alexander *et al.* (2020).

Studies were split almost evenly in their use of continuous century-scale climate simulations (i.e. modelling the transient climate change response over the next century, Table 1) or using "time slices" representative of the climate during different periods (e.g. 30-year simulations reflecting contemporary and end-of-century conditions). In the latter case, most studies used time slices less than 30 years (the canonical period over which climate conditions are defined by the World Meteorological Organization), with some using simulations as short as 10 years. While short-time slices have computational advantages, they risk aliasing or mischaracterizing higher frequency climate variability as climate change (Santer *et al.*, 2011; Deser *et al.*, 2012a; See section on simulating longer time slices or full-transient regional projections) and provide a very limited sample for gauging potential changes in the frequency of management-relevant extreme events.

Consideration of evolving methodologies over the past 25 years revealed an overall increase in studies over time with a rapid convergence on one-way dynamical downscaling approaches (Figure 4a). A gradual refinement in the horizontal resolution of downscaling frameworks is also apparent, with a significant fraction of most recent studies downscaling to resolutions finer than 5 km (Figure 4b). However, specific rationale for enhanced resolution (i.e. demonstrable improvement in skill for LMR-relevant metrics relative to coarser predecessors) was seldom given. There has also been a marked increase in the number of studies including biogeochemical dynamics (Figure 4e). Increases in the number of projections and simulation durations, however, have been more limited (Figure 4d and f) and there has been no convergence on bias correction approaches (Figure 4c).

In summary, while climate downscaling studies to date have provided diverse insights into the response of coastal ocean ecosystems to climate change, most fall short of the goal of providing accurate projections of the range of ocean futures for LMR-relevant processes and quantities (i.e. Link *et al.*, 2015). Lack of consensus on best practices also presents a challenge for defending LMR decisions based on downscaled projections, which could have significant ecological, social, and economic implications.

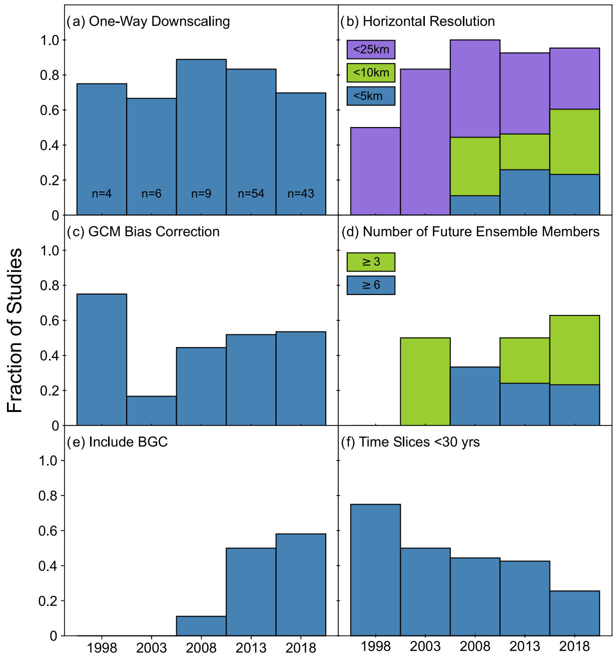

Figure 4. Chronological progression of ocean downscaling studies showing the fraction of all studies within 5-year bins that utilize: (a) one-way, dynamical methods, (b) horizontal grid resolution under 5, 10, and 25 km, (c) bias correction of GCM forcing fields, (d) future ensembles greater than or equal to three and six simulations, (e) ocean BGC, and (f) timeslice experiments less than 30 years in duration. The total number of studies (n) for each 5-year bin is indicated in panel (a).

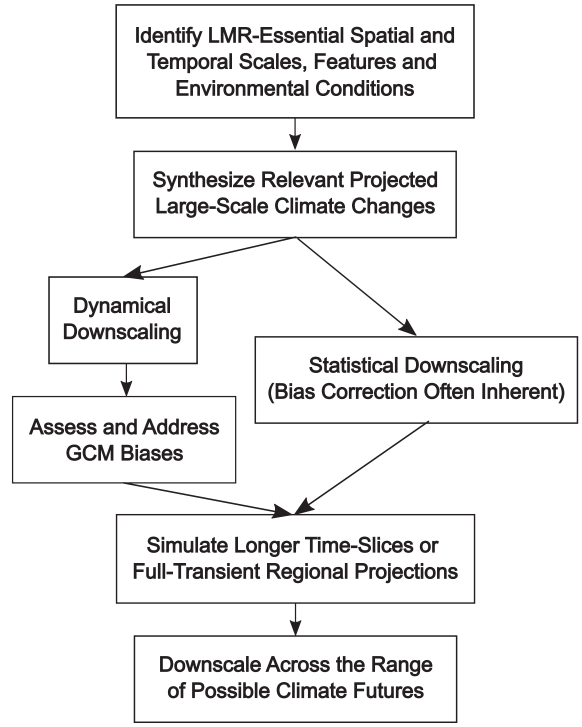

Figure 5. Schematic of the recommended ocean downscaling protocol.

A protocol for next-generation downscaling for LMR applications

Building on lessons drawn from the studies synthesized in the preceding section, we next present a protocol for climate downscaling efforts meant for LMR science and management applications in a changing climate. This protocol, which is summarized in Figure 5, is not intended to be prescriptive—approaches should ultimately be shaped by the specific objectives of each study and the resources available to meet them. Rather, the goal is to accelerate progress towards the development and adoption of robust regional ocean downscaling systems and experimental designs that can broadly support LMR science and management applications under climate change. Where needed, we delve further into the strengths and limitations of specific studies from Table S1 to support protocol elements and identify aspects in need of additional scrutiny to identify the most effective approaches.

LMR-driven design of ocean downscaling systems

LMR-motivated climate change downscaling efforts should begin by defining the decision-relevant oceanographic features, conditions, and phenomena most critical to the distribution, productivity, and sustainability of the LMRs of interest. To ensure downscaling systems ultimately yield decision-relevant information suitable for scenario planning (e.g. Borggaard *et al.*, 2019), vulnerability studies (e.g. Hare *et al.*, 2016), and formulating climate-resilient management strategies (e.g. A'mar *et al.*, 2009), this step should be jointly conducted by multidisciplinary research teams. Teams would ideally include climate scientists, physical, biological and fisheries oceanographers, fisheries economists, social scientists, stock assessment, and ecosystem modellers, managers, and stakeholders.

Resolving the ocean conditions most relevant to the LMR of interest is the primary objective of the downscaling effort and shapes all aspects of the experimental design, including resolution and resolution-dependent physical parameterizations, the components of the downscaling framework (e.g. ocean, ice, biogeochemistry, benthic habitats, land, hydrology, and estuarine/wetland components), domain extent, source of forcing and boundary conditions, simulation duration, output fields, frequency, etc. This process should carefully consider current knowledge of climate and environmental effects on LMR life histories and stock dynamics, and be refined as new mechanisms are uncovered (See section titled Next-generation ocean downscaling for marine resource applications). The added value of downscaling is also defined by the degree to which the effort resolves LMR-critical features that a GCM cannot.

This step may seem self-evident. However, as discussed in Section 3, many of the studies reviewed in Table S1 lacked clearly defined LMR-motivated oceanographic targets, instead relying on generalizations (e.g. "resolving coastal processes") that are difficult to quantify or clearly map onto LMR-management challenges. As a counter-example, Hermann *et al.* (2016) identified representation of the Bering Sea "cold pool" as a key objective for their experiments because it plays a fundamental role in shaping the productivity and distribution of Bering Sea LMRs (Stevenson and Lauth, 2019). Thus, they targeted a level of spatial refinement that permitted the dynamical emergence of this feature. Increasing resolution judiciously and not beyond the scales that are necessary to resolve

LMR-critical features is pragmatic and essential for navigating computational tradeoffs (e.g. ensemble size vs. resolution).

Given the critical role of the atmosphere on LMR-relevant ocean dynamics (e.g. coastal upwelling systems, Small *et al.*, 2015), we expect LMR-driven considerations to motivate further exploration of downscaling frameworks resolving both atmospheric and oceanic processes (e.g. Jang *et al.*, 2017). Furthermore, given a growing understanding of the importance of dynamically changing biogeochemical drivers to LMRs (e.g. acidification, Orr *et al.*, 2005; deoxygenation, Keeling *et al.*, 2010; changing productivity baselines, Steinacher *et al.*, 2010), we expect that LMR-driven design will motivate further inclusion of biogeochemical models, continuing the trend evident in Figure 4e. Similarly, the importance of freshwater and estuarine dynamics to coastal LMRs (e.g. Elliott and Hemingway, 2002), together with strong anthropogenic perturbations in these systems (e.g. Diaz and Rosenberg, 1995; Anderson *et al.*, 2002), will propel expansion of LMR-driven downscaling across the terrestrial-ocean boundary. Pioneering studies in this area include those in the Baltic Sea (Meier *et al.*, 2012a, b; Saraiva *et al.*, 2019a), where large anthropogenic increases in nutrient loading in Baltic waters and chronic hypoxia and harmful algal blooms made resolution of these drivers a high priority for LMR applications. These studies may serve as valuable templates, as we anticipate that careful consideration of LMR-critical quantities and phenomena will move downscaling frameworks in other regions towards more holistic regional earth system frameworks to meet ecosystem-based management challenges (Link, 2002; Holsman *et al.*, 2019).

Synthesize relevant projected large-scale climate changes

Once LMR-relevant environmental conditions and temporal scales are defined, a process-based synthesis of CMIP projected, basin-scale climate change for the region of interest is essential to ensuring that a plausible range of potential climate futures is considered in the downscaling system. Several efforts in Table S1 rest upon such syntheses, though their scope often covered only a small range of potential basin-scale LMR-relevant drivers: The Northwest Atlantic downscaling experiments of Alexander *et al.* (2020; Figure 3), for example, explored the range of basin-scale North Atlantic warming and the magnitude and changes of the Atlantic Meridional Overturning Circulation (AMOC) across GCMs before finalizing their downscaling strategy. The large-scale warming signal was targeted due to its role in Northwest Atlantic LMR range shifts (e.g. Nye *et al.*, 2009), while weakening AMOC under climate change had been recently linked to potential changes in water mass properties along the Northeast US shelf that could accentuate radiatively driven warming signals (Saba *et al.*, 2016). Each of the GCMs selected for downscaling reflected a self-consistent combination of these two important large-scale drivers of local changes for the Northeast US shelf. However, the large differences in salinity trends apparent in Figure 3, together with the importance of salinity trends for the timing of plankton blooms and fisheries recruitment (Platt *et al.*, 2003; Song *et al.*, 2010), suggest that further analysis of freshwater inflows and Arctic ice melt is needed to understand the scope of basin-scale changes relevant to LMRs on the Northeast US Shelf.

In a second case, Muhling *et al.* (2018) considered the range of projected local warming and precipitation signals from multiple GCMs (Figure 6) before using a hybrid statistical–dynamical downscaling approach to project changes in Chesapeake Bay salinity and temperature. This was then used to project resultant changes in habitat for bacterial pathogens that threaten the shellfish industry in the bay and pose a public health risk (Muhling *et al.*, 2017). While this approach ultimately provided a useful assessment of projected temperature and salinity changes, minimal connections to projected basin-scale responses were made. Variations in annual warming were implicitly assumed to be linked with variations in GCM's thermal sensitivity, and the annual increase in precipitation was simply noted as consistent with mean GCM responses in extratropical latitudes (e.g. Held and Soden, 2006). A deeper analysis of projected changes in the atmospheric pressure systems shaping weather patterns over Chesapeake Bay and their seasonal shifts (e.g. Scully, 2010) would provide a more complete context for interpreting projected regional changes.

The synthesis of projected large-scale climate changes and uncertainties should conclude by articulating a clear set of potential basin-scale climate futures followed by hypotheses for unresolved regional effects of these changes on coastal ecosystems and the marine resources they support. This summary can be streamlined by drawing from existing syntheses of climate model performance and projections (e.g. Christensen *et al.*, 2013, Laurent *et al.*, 2021), and past work for regions with shared large-scale climate drivers. Examples of papers that informed model choice for studies presented in Table S1 included Wang *et al.*, 2010; Overland *et al.*, 2011; Schrum *et al.*, 2016. This step can also be accelerated through the use of new web-based tools enabling rapid visualization, analysis, and subsetting of the suite of CMIP climate and earth system models (e.g. Alder *et al.*, 2013; Scott *et al.*, 2016; https://www.esrl.noaa.gov/psd/ipcc/). As an additional benefit, we anticipate that mechanistic syntheses aimed at regional applications will foster constructive exchange between the regional and global modelling communities in addressing the grand challenge of improving regional climate information.

Choose downscaling method(s)

As previously noted, one-way nested dynamical ocean modelling studies predominate Table S1 (Figure 2a). These frameworks have a number of strengths, perhaps most notably their reliance on fundamental laws of physics to make the often-complex connections between basin-scale climate forcing and shelf-scale ocean responses. The use of GCM-prescribed forcing fields ensures that perturbations across driving climate variables originate from self-consistent and co-evolved sets of the global dynamics that are broadly used and vetted by climate impacts researchers. Furthermore, one-way (as opposed to two-way coupling, Table 1) between GCMs and regional configurations does not produce new global climate/ocean simulations whose large-scale responses may depart from published projections in ways that require additional evaluation and documentation.

With these advantages in mind, we expect that one-way nested dynamical ocean modelling studies will continue to play a key role in future LMR-focused climate change efforts. However, this approach still poses a significant computational cost that has limited the number of downscaled projections (Figure 2d), and an ocean-only framework limits study of potentially LMR-critical phenomena that may be rooted in atmospheric or terrestrial/freshwater processes. Future efforts should consider the possibility that alternatives to, or in combination with, "standard" one-way ocean downscaling may best achieve the LMR-driven goals laid out in the first step of the protocol (LMR-driven design of ocean downscaling systems). To spur such investigation, we discuss the strengths and

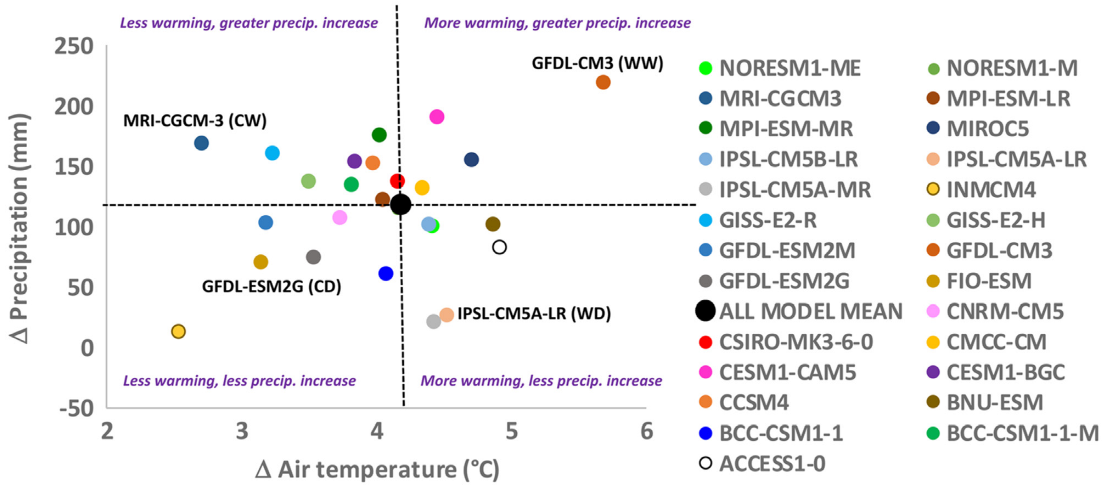

Figure 6. Example of identifying GCMs that span the range of possible LMR-relevant futures: Muhling *et al.* (2018) chose 4 out of 26 GCM projections that spanned the range of 2-meter air temperature and total precipitation anomalies for the Susquehanna River watershed under RCP8.5: 1956–2005 versus 2050–2099. The ensemble mean from all GCMs is shown in black and extended to both axes with the black dashed line. The four GCMs chosen to represent the range of potential futures for the Chesapeake Bay are labelled with the text. From Muhling *et al.* (2018) reproduced with permission from Estuaries and Coasts.

weaknesses of prominent alternatives below, drawing from examples in Table S1.

Empirical statistical downscaling

Many empirical statistical downscaling (ESD) methods have been used to refine GCM results, particularly in atmospheric and hydrological communities (Fowler *et al.*, 2007), but also in the marine realm (Table S1). The key requirement is a long (preferably multidecadal) time-series of observations for the variable of interest in order to capture seasonal, interannual, and decadal variability. While terminology for these techniques varies across scientific groups, ESD methods broadly operate by ingesting three inputs: contemporaneous historical observations and historical model output, and model output for a future period. Statistical relationships linking these fields are generated and used to produce refined future data products (Hewitson and Crane, 1996).

The strength of ESD methods lies in the ability to rapidly construct large ensembles of projections from dozens of climate models if robust statistical relationships can be found. However, the diversity (e.g. quantile mapping, machine learning, etc.) and complexity of ESD formulations mean different methods may yield dissimilar results even when presented with identical inputs. For example, metrics related to the tails of a climate variable's distribution (e.g. return period lengths, magnitudes of extreme events), weather sequences and spells, the representation of low-frequency variability, and whether the GCM's climate change signals are preserved, can all vary markedly across results produced by different ESD methods (e.g. Wilby and Wigley, 1997; Fowler *et al.*, 2007). Several overviews provide information that can help guide applied researchers in their use of ESD data products (e.g. Wilby and Wigley, 1997; Ekström *et al.*, 2015; Maraun and Widmann, 2018).

ESD methods should not be viewed as a panacea for dynamical model shortcomings. Many, for example, make assumptions of stationarity (i.e. future relationships between coarse and fine-scale features will remain the same), which may be problematic for climate change applications (Dixon *et al.*, 2016; Lanzante *et al.*, 2018). However, informed use of ESD processing has the potential to complement uncertainty assessments from dynamical approaches in data-rich shelf ecosystems, or those which benefit from highly accurate observation-based ocean reanalysis products. It is notable, for example, that the study with the largest number of projections in Figure 2d employs statistical approaches (Hermann *et al.*, 2019).

Burgeoning applications of machine learning within ESD frameworks used for marine resource questions show promise. Muhling *et al.* (2018) used model trees, a machine learning algorithm, to predict Chesapeake Bay surface temperature and salinity. However, similar to less sophisticated ESD methods, machine learning techniques entail their own challenges (e.g. overfitting and a climate stationarity assumption) and are most skillful when supplied with an abundance of training data. For this reason, they are more common in non-marine applications (e.g. Gaitan and Cannon, 2013; Gaitan *et al.*, 2014) and will likely be most successful when used to study highly observed ocean systems.

Hybrid dynamical–statistical approaches

Hybrid dynamical–statistical approaches have been developed to combine the data-driven and computational strengths of statistical approaches with the mechanistic strengths of dynamical frameworks: Muhling *et al.* (2018) linked estuarine surface temperature and salinity anomalies in the Chesapeake Bay to projected warming and precipitation changes in GCMs by combining statistical relationships and a simple yet mechanistic water balance model (Figure S3). In the Bering Sea, Hermann *et al.* (2019) used multivariate statistics (i.e. empirical orthogonal functions) and a small ensemble of dynamically downscaled projections to identify dominant modes of regional oceanic response to changes in atmospheric forcing. Then, by projecting atmospheric forcing from a much larger GCM ensemble onto these modes, an approximation of full dynamical downscaling results was obtained, which spans a wider range of projected changes across GCMs and greenhouse gas scenarios. Machine learning could potentially be useful in this hybrid approach if it could provide a compact analogue of the regional model's response to a wide variety of global forcings. Lastly, dynamical regional models have also been forced with statistically downscaled global atmospheric fields as a means of addressing biases and shortcomings that result from coarse GCM resolution. This and other pre-processing methods are addressed in greater detail in the context of bias correction in the next section of the protocol.

Two-way nesting

Unlike "one-way" methods and ESD, "two-way" dynamical nesting between a regional downscaling framework and either a coarser, ocean-only domain or fully coupled GCM allows information from the refined ocean solution to propagate back to the coarser simulation. Two-way designs can reduce inconsistencies between the regional and GCM solutions. These inconsistencies can result in spurious artifacts within, and at the boundary of, the "child" domain (Table 1), and are more broadly problematic when regional domains encompass important aspects of the basin-scale climate system (e.g. western boundary currents) that could significantly impact the GCM solution.

The costs of "two-way" dynamical downscaling, however, includes the need to run a larger global simulation alongside each regionally refined simulation. Two-way nesting must establish complex software infrastructure to pass information back and forth with any model to which it is coupled. These technical and computational challenges of two-way nesting and unstructured grids may be particularly cumbersome for LMR applications since downscaling multiple GCMs is critical for spanning the range of potential ocean futures (e.g. Hawkins and Sutton, 2009; Frolicher *et al.*, 2016). However, targeted efforts are useful in understanding the consequences of the simplifications inherent to "one-way" approaches.

We note that GCMs incorporating unstructured or stretched grid capabilities (e.g. Ringler *et al.*, 2013) provide a second means of achieving regional refinement and allowing feedbacks between finer- and coarser-resolution domains. These approaches, however, present similar challenges for climate impacts studies as two-way nesting: one must absorb the added computational cost of global coverage, and generating a multi-GCM ensemble to span the range of ocean futures would require multiple GCMs with comparable regionally refined configurations. Unstructured and stretched grid approaches also raise the challenge of developing flexible parameterizations of sub-grid scale processes accounting for large contrasts in resolution within the same model domain (Danilov, 2013).

Assessing and addressing GCM biases

As discussed earlier (Hard-won regional climate fideltiy gains for global models) GCMs exhibit regional biases and shortcomings linked to resolution and simulation design that will likely remain a challenge for regional climate impacts studies. Dynamical ocean downscaling alone can reduce biases resulting from unresolved regional processes through finer-scale solutions and improved parameterizations of smaller scale physics (e.g. Kerkhoff *et al.*, 2014). However, regional GCM biases may still propagate across ocean and atmospheric boundaries of the nested domain and compromise the internal solution (Figure 7). Downscaling can even exaggerate GCM biases and artificially increase the spread of regional model projections (Bukovsky *et al.*, 2013; Hall, 2014).

Most ESD methods are designed to address deficiencies associated with both the coarse GCM resolution and biases. That is, correcting for bias is considered as critical an element of "added value" as downscaling. As described in the section on past regional downscaling studies, this view has been less universally adopted within the dynamical downscaling community (i.e. Figs. 2c and 4c). This partly reflects the possibility that refined resolution may be enough to ameliorate biases. It also reflects a recognition that any additional corrections applied to large-scale GCM fields does, strictly speaking, compromise the dynamical consistency of the GCM-regional model coupling, potentially eroding a key advantage of dynamical over statistical downscaling approaches. Nonetheless, the potential severity of regional GCM biases (Figure 7) and the continued challenge that they pose suggest that the cost of some compromise on dynamical consistency should be carefully weighed against the considerable potential benefits of bias correction. In the context of LMR's: how strongly do biases interfere with the reasonable manifestation of, and changes in, LMR-critical ocean features?

A critical impediment to the effective application of bias corrections in dynamical downscaling efforts is the lack of recognized "best practices" and objective criteria to define them. Furthermore, the extremely simple methods currently applied (e.g. climatological delta corrections or change factors, Table 1) differ significantly in the information about past and future climate/changes that is passed to the regional solution. More sophisticated bias correction approaches have been developed based on the same principles as the simple delta- and change-factor methods used in most studies. Time-varying delta methods, for example, can address higher order climate variability moments (e.g. Kerkhoff *et al.*, 2014). Similarly, Machu *et al.* (2015) downscaled GCM atmospheric fields by using multiple linear regressions of EOFs (Goubanova *et al.*, 2011) to generate high-resolution forcing conditions for a regional ocean model of the Benguela Eastern Boundary Current. Techniques applied in ESD (see references in Choose downscaling method(s)) may offer innovative new directions. If done effectively, bias corrections may provide a crucial and lasting element of the "added value" of regional climate downscaling for LMR applications.

Simulate longer time slices or full-transient regional projections

When downscaling ocean conditions for the purpose of inferring LMR climate change implications, it is important to generate sufficiently long time periods of downscaled information. At regional scales, natural climate variability can dominate climate signals, sometimes generating multidecadal cycles, which, when analyzed over too short timeframes, can be misattributed to anthropogenically driven climate change (e.g. Deser *et al.*, 2012a, b) or result in overestimation or underestimation of future changes. We illustrate this issue in Figure 8 wherein we compare projected change in SST for the Gulf of Alaska using end members from the NCAR CESM large ensemble (Kay *et al.*, 2015). The ten-year means of individual ensemble members give widely different results, with projected SST changes differing by more than 1.5°C in some regions (Figure 8a and e). In comparison, the 30-year means (Figure 8b and f) have a smaller range of 1°C or less; these longer time slices are less influenced by spurious trends arising from low-frequency climate modes and noise produced by other internal climate varia-

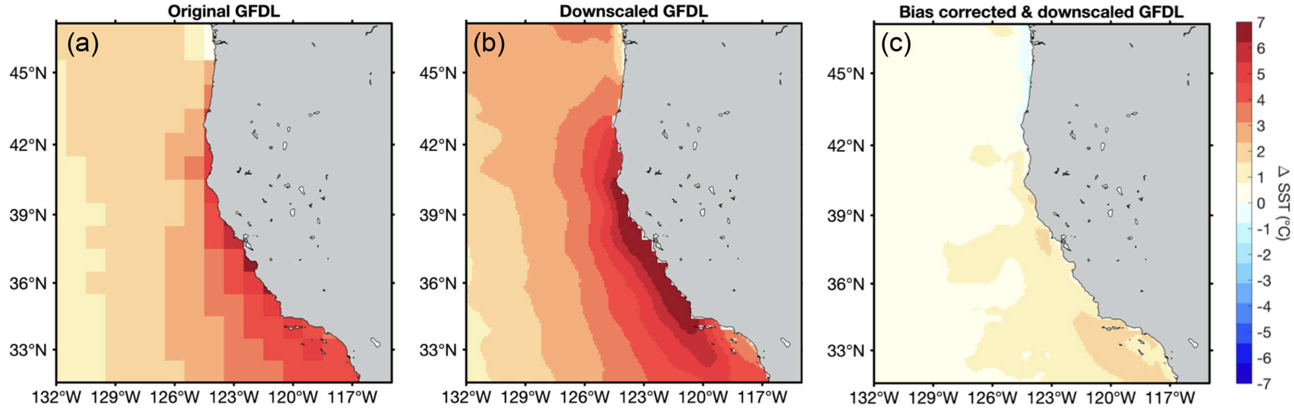

Figure 7. Illustration of downscaling model improvement with GCM bias correction: Average summer (JJA) SST bias from 1982 to 2005 with respect to the one-fourth daily NOAA OISST observations for (a) the original GCM output; (b) the GCM dynamically downscaled by a regional model; and (c) the same framework as in (b) but with a "time-varying" delta to correction applied to the GCM forcing fields (see Pozo Buil *et al.*, 2021 for model details).

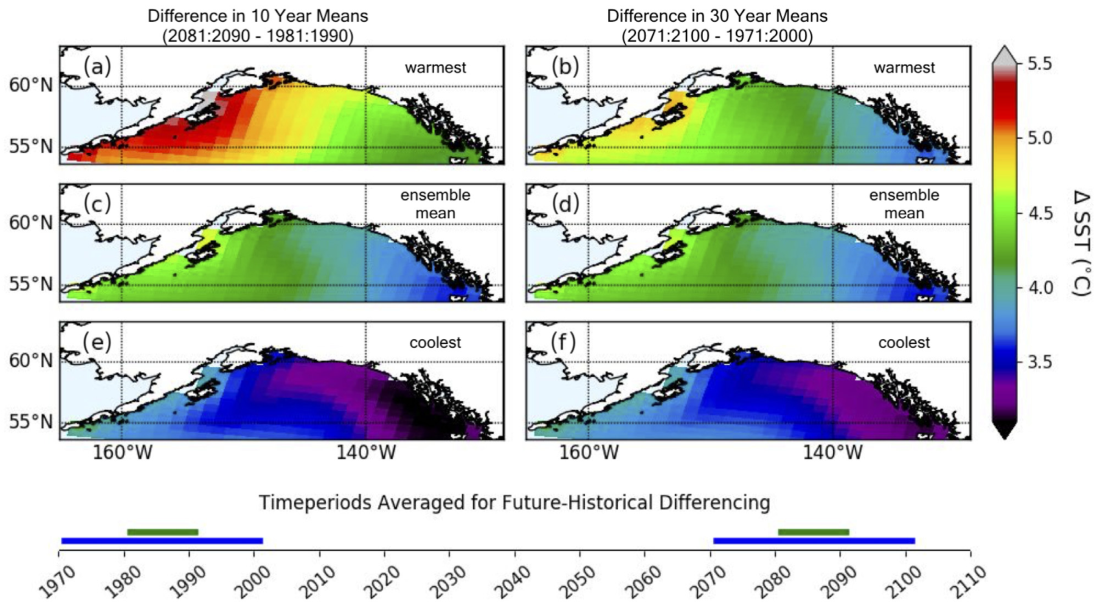

Figure 8. Illustration of the risk of climate signal aliasing when downscaling too short timeslices: Using ensemble members from the NCAR Large Ensemble Community project, we illustrate how the spread (i.e. internal variability) in Gulf of Alaska SST-change is larger when considering 10- (left-hand panel) vs. 30-year means (right-hand panel). Top plots (a, b) depict the greatest increase in SST (warmest), bottom plots (e and f) show the smallest increase (coolest), while the centre plots represent the ensemble mean (35 members analyzed in total). The increased spread of the 10 year relative to 30-year averages reflects the aliasing of climate fluctuations onto climate change signals that one would expect from using 10-year time slices.

tions. Note that this issue can also be solved by taking the average of many ensemble members (Figure 8c and d). In addition to reducing the potential for higher frequency climate variability to overwhelm signals associated with climate change, longer (and more) simulations increase the capacity to analyze environmental extremes that can have profound impacts on marine resources (e.g. spawning-food resource mismatches associated with extreme anomalies in seasonal transitions; Cushing, 1990; Asch *et al.*, 2019). Additional years allow climate-driven changes in the frequency of such events to be better characterized. Longer time slices also ameliorate artifacts caused by adjustments to new forcing (i.e. model spin-up, often $<$ 5 years). The stabilization time period increases for models simulating physical processes in intermediate depth waters or biogeochemically complex benthic processes (e.g. Kearney *et al.*, 2020). For these reasons, we recommend running longer (at least 30 years, post-spin-up) "time slices" if taking a representative-period approach, or downscaling the full progression of climate changes over the historical period and the next century (i.e. simulate the full "transient climate response," Table 1).

While quantifying the magnitude of long-term differences (e.g. end-of-century vs. present) gives some insight into the potential implications for future marine habitat suitability, this method of assessing environmental change neglects the interim progression of ocean conditions. Many marine species have physiological thresholds that can result in nonlinear responses to climate change, which will likely be missed if only comparing two distant periods. Simulations capturing the transient climate change signal allow for assessment of the time integration of climate change and variability effects that shape populations leading up to the time period of interest. This approach is recommended if computational resources allow it without severely compromising other goals. If the time slice approach is well-executed with 30-year periods (i.e. timeframe selections guided by sensitivity analyses and adequate spin-up), the savings are rather marginal compared with a 120-year transient simulation.

Downscale across the range of climate change uncertainty

Robust marine resource management strategies necessitate considerations of the range of possible ocean futures (Link *et al.*, 2015). However, most studies in Table S1 produce only a small number of future ensemble members (Figure 2d). Addressing this limitation needs to be a central element of future downscaling efforts if they are to fully transition from scientifically useful experiments to robust policy and management tools.

Dynamically downscaling projections for every GCM (>50 GCMs contributed to CMIP5, Flato *et al.*, 2013; >100 registered for CMIP6, Eyring *et al.*, 2016) and greenhouse gas scenario (CMIP6 focused on five Shared Socioeconomic Pathways in select combination with four RCPs; O'Neill *et al.*, 2016) would be computationally prohibitive, particularly if consideration of a range of regional change scenarios (e.g. watershed management) were also required (e.g. Meier *et al.*, 2011a, b). Furthermore, this approach is likely inefficient because dominant sources of uncertainty in global climate change projections (model/GCM uncertainty, greenhouse gas scenarios, and climate variability) vary by region and projection time horizon (Figure S2; Hawkins and Sutton, 2009; Frölicher *et al.*, 2016), and shared algorithms and parameterizations among GCMs result in non-independent solutions (Knutti *et al.*, 2013). Therefore, strategic selection of a limited number of parent GCMs and scenarios is recommended in order to capture climate change uncertainty.

The synthesis of projected basin-scale climate futures provided by step 2 of this protocol (Synthesize relevant projected large-scale climate changes) provides a robust foundation from which to build a computationally manageable ensemble that efficiently captures the range of projected futures. From this mechanistic starting point, numerous clustering strategies, and other algorithms have been proposed to select the minimum number of models that adequately captures the range of uncertainty space (e.g. Ross and Najjar, 2019, and references therein; Muhling *et al.*, 2018; Figure 6). Ross and Najjar (2019), for example, evaluated algorithms for identifying and selecting parent GCMs with distinct changes and found that a small number of GCMs (≤ 8) was often sufficient to represent the majority (>50%) of model uncertainty for a given emission scenario in the CMIP5 dataset, though this varied somewhat by region.

Several previous studies have explored GCM selection for downscaling and model weighting based on the fidelity with regional patterns (e.g. Giorgi and Mearns, 2002; Hollowed *et al.*, 2009; Payne *et al.*, 2016). However, the connection between a GCM's performance in a small region and the quality of its global climate projections is tenuous (Stock *et al.*, 2011, and references therein). Furthermore, producing skill-weighted composite projections (e.g. Liu *et al.*, 2015), or equally weighted ensemble means (e.g. Cordeiro Pires *et al.*, 2016) generated from multiple global models will reduce the dynamical consistency of climate model projections (i.e. the resulting combination of climate states may be "physically implausible," Knutti *et al.*, 2010). In other cases, the importance of specific modes of climate variability to regional marine resource responses has prompted researchers to prioritize the selection of models that skillfully represented those modes. Hermann *et al.* (2016), for example, prioritized models with a reasonable representation of the Pacific Decadal Oscillation (PDO) because the PDO modulates the Bering Sea cold pool and there was an interest in understanding how climate change and PDO variations will combine to determine future states. Similarly, Saba *et al.* (2012) prioritized models with skillful ENSO simulations to explore how climate change would interact with ENSO variability to impact endangered leatherback sea turtle populations. However, (un)skillful simulation of specific climate variability modes is not inherently indicative of a GCM's ability to represent broader climate change sensitivity and other important regional processes (e.g. Knutti, 2008; Knutti *et al.*, 2010). Thus, to prioritize covering the range of climate change of potential futures under climate change, we recommend limiting model selection based on regional skill to only culling GCMs with flaws so severe that they prevent meaningful interpretation of even bias-corrected downscaled simulations (Overland *et al.*, 2011).

GCM data availability is an underappreciated yet critical consideration that often dictates model choice and impedes uncertainty assessments. As an example, Table S2 indicates the number of climate modelling centres that contributed historical and scenario (RCP8.5) simulations to CMIP5 at specified temporal resolutions. Invariably, the number of GCMs with information relevant to this specific climate change comparison is smaller than the total number of broadly participating centres, with data availability at the higher temporal frequency being particularly sparse (e.g. Naughten *et al.*, 2018). Obtaining GCM output that extends beyond standard CMIP diagnostics (e.g. higher temporal resolution) for regional boundary and forcing conditions requires close relationships with a global modelling centre and colleagues at such centres willing to generate and provide high-resolution model output. Removing such dependencies is critical because they inherently limit options for exploring GCM-contributions to climate change and downscaling uncertainty. Table S2 also suggests enhancements to CMIP diagnostics to facilitate use in ocean downscaling studies. Both minimum and best possible temporal frequencies are provided, recognizing that data serving constraints may impede efforts to achieve the latter aspirational targets.

Most studies in Table S1 focused on spanning the uncertainties associated with GCMs and scenarios, drawing upon well-established theoretical frameworks for parsing the often considerable uncertainty in these projections into that associated with climate model formulations, greenhouse gas emissions, and climate variability (Figure S2). Few (e.g. Holt *et al.*, 2016; Muhling *et al.*, 2018) explored uncertainty from downscaling methods or modelling frameworks by employing more than one downscaling technique, physical ocean model, or BGC model. It is unclear whether uncertainty due to downscaling method is as important a consideration for ocean physics/biogeochemistry as in atmospheric studies (e.g. Murphy, 1999; Huth, 2004; Wood *et al.*, 2004; Bürger *et al.*, 2012). However, projection spread due to disparities in vertical coordinate and mixing schemes (e.g. Luneva *et al.*, 2019), as well as BGC algorithms could be comparable. Further exploration of these uncertainties is needed, but should be approached judiciously given the considerable investment required to explore large uncertainties associated with global climate change projections, and may be better suited to larger efforts (e.g. CORDEX, Giorgi *et al.*, 2009; NARCCAP, Mearns *et al.*, 2009) that utilize numerous regional climate models (RCMs). Regardless, clear methodological schematics (e.g. Figure 2 in Saraiva *et al.*, 2019b) that comprehensively depict the modelling workflow facilitating communication of uncertainty sources to better inform LMR managers and stakeholders.

Next-generation ocean downscaling for marine resource applications

Projections of the range of potential coastal ocean futures at the scales of LMR management can inform strategy evaluations and contribute to long term LMR-management plans under climate change scenarios. While GCMs have made critical contributions in this regard and continue to improve, they will still have significant limitations for regional LMR applications. Specifically, the resolution of coastal physical and biogeochemical processes critical to LMRs will continue to be hampered by the computational constraints imposed by century-scale global simulations. Efforts to reduce regional GCM biases will continue to be challenged by the "free-running" nature of global climate change projections and the need for GCMs to prioritize globally robust over regionally optimal formulations. Provision of GCM outputs will continue to be encumbered by data storage and dissemination challenges. Climate downscaling has the potential to address the limitations of GCM projections for LMR applications, but only with improvements relative to past efforts.

Our suggested protocol for future climate downscaling efforts emphasizes conscious LMR-driven design of downscaling frameworks to ensure the production of decision-relevant information. This is likely to push regional ocean-sea ice downscaling methods toward earth system frameworks, including critical atmospheric, biogeochemical (e.g. acidification, deoxygenation), and terrestrial/freshwater (e.g. eutrophication) LMR drivers. The protocol emphasizes downscaling multiple projections that span the range of possible ocean futures, with durations long enough to confidently capture climate change signals and characterize extreme events. Ensemble projections should be efficiently built by drawing upon a comprehensive synthesis of projected large-scale trends across GCMs and scenarios. This prioritization demands the judicious refinement of regional model resolution, with pragmatic consideration of decision-relevant features and phenomena superseding generic arguments (i.e. higher resolution is needed to resolve "coastal processes"). It also emphasizes the creative application of empirical statistical downscaling approaches to augment more computationally expensive dynamical methods. Such approaches may be particularly useful in relatively well-observed nearshore regions that would require very high resolution (< 1 km) to capture dynamically. The protocol recognizes bias correction as a key component of the potential value of climate downscaling that will continue to be needed despite GCM improvement. There is a need, however, for improved approaches and objectively defined best practices to achieve these benefits of addressing GCM biases while minimizing dynamical compromises.

The outlined steps would yield regional ocean projections to robustly support LMR management plans, strategy evaluations, and risk assessments (e.g. Holsman *et al.*, 2017), LMR vulnerability assessments (e.g. Hare *et al.*, 2016; Lettrich *et al.*, 2019), and scenario planning (e.g. Borggaard *et al.*, 2019) in a changing climate. The regional modelling frameworks developed through this protocol would also be useful for decisions on shorter sub-seasonal to decadal time-scales (Payne *et al.*, 2017; Tommasi *et al.*, 2017), building on prototype regional ocean sub-seasonal to decadal prediction systems developed for numerous regions (e.g. Siedlecki *et al.*, 2016; Ross *et al.*, 2020). Elements of the protocol itself are generally applicable to seasonal-to decadal efforts as well, particularly the need to prioritize LMR-relevant ocean features and span the range of projection uncertainty. However, the criteria for designing ensembles and correcting biases to achieve the latter would likely differ from those produced for multidecadal projections, as differences between climate change scenarios are less consequential (Hawkins and Sutton, 2009; Frölicher *et al.*, 2016). Furthermore, while biases in seasonal-to-decadal predictions are reduced relative to multidecadal climate projections through data assimilation techniques used to initialize predictions, model drift away from these initialized states must instead be addressed (e.g. see Figure 1 of Tommasi *et al.*, 2017 and associated discussion). Regardless, in order for such predictions to translate to management decisions, they must be effectively disseminated to scientists and management frameworks capable of translating the outputs they provide into improved tactical and strategic decisions. These steps pose challenges as diverse and formidable as those addressed herein.

Projections spanning the range of potential climate futures for LMR-relevant scales and phenomena will produce large amounts of model output that need to be made available to LMR scientists, managers, and other stakeholders. However, the storage, curation, and dissemination of these multiterabyte datasets present a formidable and costly data management challenge. While there are a number of tools for facilitating remote data access (e.g. HTTP, OPeNDAP) and growing cloud resources, a fundamental bottleneck to the process is sufficient, secure, and sustained digital storage. The necessary infrastructure to accomplish this requires substantial financial investment and, thus moving forward, we recommend considering and incorporating funding for data storage and dissemination into the development of new ocean downscaling research projects. Furthermore, the fragmentation of downscaling efforts, regional modelling systems, and component models reflected in Table S1 has led to similarly fragmented model output variables, variable names, and output frequencies. These challenges have significantly impeded the translation of ocean projections to marine resource applications. We suggest the adoption of CMIP diagnostics as a common core set of variables (Table S2) across regional downscaling studies. These can be augmented by region-specific, LMR-relevant metrics derived via the co-development of regional downscaling systems (See section on LMR-driven design of ocean downscaling systems). Such products can be served through established web portals (e.g. Scott *et al.*, 2016) or leverage burgeoning cloud computing capacity for dissemination and analysis capacity. The establishment of national and international communities of practice, facilitated by international marine science organizations (e.g. ICES, PICES), could accelerate these developments, as well as convergence on other key aspects of climate downscaling approaches for LMR applications.

Once effective dissemination pathways are established, the outputs must be integrated with management systems capable of translating outputs to improved management planning. Climate impacts on LMRs are complex and varied, including direct effects on physiology, behaviour, distribution, and vital rates as well as indirect impacts on energy flow pathways and species interactions (Hollowed *et al.*, 2013; Payne *et al.*, 2017; Tommasi *et al.*, 2017, and references therein). Furthermore, emergent responses of LMRs to climate variability and climate change have to be identified while considering the effects of other, potentially additive stressors acting on coastal ecosystems, such as fishing, habitat loss, offshore wind energy development, and pollution. Similarly, complex interactions impact marine pathogens and harmful algal blooms (e.g. Burge *et al.*, 2014; Wells *et al.*, 2020). While considerable progress has been made, limited understanding of these interactions remains a significant impediment to the integration of climate information and management decisions (e.g. Skern-Mauritzen *et al.*, 2016). Increasing understanding of this mosaic of interactions places a premium on sustained monitoring, laboratory experiments, and process-based studies. Retrospective ocean simulations with modelling frameworks developed for downscaling climate projections can complement these information sources, providing additional insight into the mechanisms underlying past fluctuations.

While uncertainties in the response of LMRs to environmental conditions pose challenges to the integration of climate information into current LMR management approaches, in light of recent extreme events (e.g. Bond *et al.*, 2015), LMR managers and stakeholders are recognizing the need to assess and develop adaptation strategies for climate impacts on LMRs and the fishing communities that depend on them (Pinsky and Mantua, 2014; Karp *et al.*, 2019). LMR managers and stakeholders are accustomed to operating in an uncertain environment, and scientific tools, such as management strategy evaluations (MSEs), have been developed to assess the performance of management strategies relative to a set of stakeholder objectives under a range of uncertainties (Punt *et al.*, 2016). For some species, emerging capacities to explicitly resolve climate effects on LMRs and to integrate climate projections into LMR models are now enabling performance assessment of management strategies including climate uncertainty (e.g. A'mar *et al.*, 2009; Gaichas *et al.*, 2016; Hollowed *et al.*, 2020; Holsman *et al.*, 2020, and references therein). Further development of methods to fully address diverse sources of uncertainty in MSEs, however, is needed (e.g. Payne *et al.*, 2016; Szuwalski and Hollowed, 2016; Karp *et al.*, 2019). Such efforts may require consideration of LMR models spanning a range of complexity (e.g. Kaplan *et al.*, 2019; McHenry *et al.*, 2019; Hollowed *et al.*, 2020), expanding the ensemble of climate projections discussed above to include a broader range of LMR outcomes (Reum *et al.*, 2020b) and placing a premium on effectively communicating uncertainty to stakeholders. In cases where quantitative estimates are not available, estimates of additional risk can be qualitatively assessed through vulnerability assessments (e.g. Colburn *et al.*, 2016; Hare *et al.*, 2016) based on downscaled projections of potential ocean futures (e.g. Spencer *et al.*, 2019), qualitative network analysis (e.g. Reum *et al.*, 2020a), or risk tables (e.g. Dorn and Zador, 2020).

By providing more accurate estimates of uncertainty, ensembles of downscaled projections present an opportunity to expand and improve the effectiveness of such approaches. For example, they will allow for more robust testing of non-stationary reference points. Availability of fine-scale ocean data is particularly important for environmentally informed, spatially explicit LMR models linked to fleet dynamics models (e.g. Haynie and Pfeiffer, 2012; Le Bris *et al.*, 2018; Smith *et al.*, 2020). Such models require a heightened understanding of fleet dynamics and socioeconomic drivers, which can vary significantly across fisheries (e.g. Colburn *et al.*, 2016; Watson and Haynie, 2018). Advancing the integration of socioeconomic considerations with LMR models is also central for probing interactions between LMRs and other coastal developments on climate change time-scales (e.g. wind farms). The combination of these LMR science and management advances, together with robust climate information from the downscaling frameworks discussed herein, would enable the development of robust long-term strategic plans to promote the well-being of fishing communities in the face of increased climate risk due to shifts in LMRs distributions (e.g. Kleisner *et al.*, 2017; Pinsky *et al.*, 2018).

Sustaining marine resources in a changing climate is a daunting, cross-disciplinary challenge. However, pioneering efforts over the past two decades have provided ample insights and built the scientific communities that, in combination with technological advances, can enable regional ocean projections to robustly support tactical and strategic LMR management under climate change, if continued commitments are made to the development of management frameworks capable of translating this information into improved decisions.

Supplementary data

Supplementary material is available at the *ICESJMS* online version of the manuscript.

Data availability statement

The data underlying Figures 3 and 4 are available in the online supplementary material (Table S1); the data for Figure 8 were accessed from the NCAR large ensemble community project (Kay *et al.*, 2015). The derived data generated in this research will be shared on a reasonable request to the corresponding author.

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