Future temperature and salinity in Puget Sound, Washington State, under CMIP6 climate change scenarios

Stevie Walker (steviewalker99@gmail.com)
Boston College https://orcid.org/0000-0001-9503-1157

Hem Nalini Morzaria-Luna
Long Live the Kings

Isaac Kaplan
NOAA NWFSC: NOAA Fisheries Northwest Fisheries Science Center

David Petatán-Ramírez
Universidad Autónoma de Baja California Sur: Universidad Autonoma de Baja California Sur

Research Article

Keywords: puget, sound, future, salinity, temperature

Posted Date: September 21st, 2021

DOI: https://doi.org/10.21203/rs.3.rs-905960/v1

Version of Record: A version of this preprint was published at Journal of Water and Climate Change on December 6th, 2022. See the published version at https://doi.org/10.2166/wcc.2022.282.

Abstract

In Washington State, climate change will reshape the Puget Sound marine ecosystem through bottom-up and top-down processes, directly affecting species at all trophic levels. To better understand future climate change effects on sea surface temperature and salinity in Puget Sound, we used empirical downscaling to derive high-resolution time series of future sea surface temperature and salinity. Downscaling was based on scenario outputs of two coarse-resolution General Circulation Models, GFDL-CM4 and CNRM-CM6-1-HR, developed as part of the Coupled Model Intercomparison Project Phase 6 (CMIP6). We calculated 30-year climatologies for historical and future simulations, calculated the anomalies between historical and future projections, interpolated to a high resolution, and applied the resulting downscaled anomalies to a Regional Ocean Modeling System (ROMS) time series, yielding short-term (2020–2050) and long-term (2070–2100) delta-downscaled forecasts. Downscaled output for Puget Sound showed temperature and salinity variability between scenarios and models, but overall, there was strong model agreement. Model variability and uncertainty was higher for long-term projections. Spatially, we found regional differences for both temperature and salinity, including higher temperatures in the South Basin of Puget Sound and higher salinity in the North Basin. This study is a first step to translating CMIP6 outputs to higher resolution predictions of future conditions in Puget Sound. Interpreting downscaled projections of temperature and salinity in Puget Sound will help inform future ecosystem-based management decisions, such as supporting end-to-end ecosystem modeling simulations and assessing local-scale exposure risk to climate change.

1 Introduction

Continuing emissions of fossil fuels and increasing land use are changing Earth's climate in rapid and unprecedented ways (Hayhoe et al. 2017). In recent decades, anthropogenic climate change has had increasing effects on the ocean; ocean warming, ocean acidification, and ocean deoxygenation are three primary stressors that are impacting ocean biogeochemistry globally (Gruber 2011; Bopp et al. 2013). Increasing ocean temperature can change the rate of biological processes (Bopp et al. 2013), decrease species fitness (Mora et al. 2013), and cause species distribution shifts (Grieve et al. 2016; Petatán-Ramírez et al. 2019). Circulation changes are expected as well, since warmer surface oceans will result in a more stratified water column in the open ocean (Gruber 2011), though nearshore and estuarine dynamics may be more complex. Additionally, higher temperatures result in decreased ocean solubility and the creation of more hypoxic areas (oxygen minimum zones) (Keeling et al. 2010; Gruber 2011; Mora et al. 2013). Marine absorption of CO_2 is lowering overall ocean pH and carbonate availability (acidification), making it more difficult for calcifying organisms to build their shells (Doney et al. 2009; Kroeker et al. 2013; Busch and McElhany 2016). The combination of impacts on ocean biogeochemistry and additional climate change-related stressors has synergistic effects on marine ecosystems that vary by region, including altered food-web dynamics, community composition, and energy flows, as well as a potential reduction in the ecosystem services provided by marine systems (Gruber 2011; Doney et al.

2012; Popova et al. 2016). In order to develop effective mitigation and conservation strategies, climate change impacts must be investigated further on a regional and local basis (Marshall et al. 2017).

Puget Sound, a large fjordal estuarine system within the Salish Sea on the North American Pacific coast, faces many climate change-related impacts. Here, increasing temperatures are projected to result in earlier and reduced spring snowmelt, shifts in timing and intensity of upwelling, species distribution changes, decreased salmon migration and survival, and increased bloom seasons for harmful algal bloom species (Reum et al. 2011; Moore et al. 2015; Daly and Brodeur 2015; Khangaonkar et al. 2019). Coastal acidification is being exacerbated in Puget Sound (Bianucci et al. 2018), and hypoxic water area is projected to increase from <1% to 16% (Khangaonkar et al. 2019). These changes are expected to have negative impacts at multiple trophic levels, including for Chinook salmon (*Oncorhynchus tshawytscha*), coho salmon (*Oncorhynchus kisutch*), and Southern Resident orcas (*Orcinus orca; Southern Residents hereafter*) - three culturally and ecologically important species in the region (Colby 2018; Morzaria-Luna et al. 2019; Southern Resident Orca Task Force 2019). In particular, the anticipated decline in Chinook salmon could be detrimental for Southern Residents, which rely on Chinook salmon as their primary food source (Ford et al. 2010). Puget Sound faces a myriad of additional interacting anthropogenic impacts that will cause ecological, physical, and biogeochemical changes (Blackmore et al. 2019).

The complexity of these changes reflects the need for improved climate modeling techniques that can help describe potential local-scale impacts of climate change and develop informed climate policy (Ekström et al. 2016; O'Neill et al. 2016; Tommasi et al. 2017). Rapidly advancing climate modeling approaches are allowing for more detailed predictions about the future of Earth's climate. The latest projections on climate change come from General Circulation Models (GCMs) from the Coupled Model Intercomparison Project (CMIP), a major internationally-coordinated effort to provide climate projections based on a variety of emissions and land use scenarios (O'Neill et al. 2016; Juckes et al. 2020). The results from CMIP are used by the Intergovernmental Panel on Climate Change (IPCC) to inform global synthesis reports and create mitigation and adaptation strategies (O'Neill et al. 2016). Now in its sixth phase, CMIP6 includes 23 endorsed and independently-led model intercomparison projects (Eyring et al. 2016), which will be used in the upcoming IPCC assessment report (AR6), to be released in 2022. GCMs are based on fundamental equations of physics and are dynamically coupled to include atmosphere-ocean interactions, biogeochemical cycling, land and sea ice, and soil and vegetation (Hayhoe et al. 2017; Daron et al. 2018).

Because GCMs have a coarse resolution (25-300 km), downscaling techniques must be used to obtain results at higher resolutions that are applicable at regional and local scales (Hayhoe et al. 2017). Downscaling involves translating information from GCMs to achieve finer spatial- and temporal-scale dynamics, and there are three main downscaling techniques used (Stock et al. 2011; Ekström et al. 2015). In dynamical downscaling, initial and boundary conditions for Regional Climate Models (RCMs), which explicitly model physical processes but with a smaller, more accurate grid box size (1-50 km), are supplied by a GCM (Hayhoe et al. 2017; Tommasi et al. 2017). Dynamical downscaling is useful for

modeling unprecedented and rapidly changing climate conditions, but can sometimes inherit regional biases from GCMs (Stock et al. 2011; Tommasi et al. 2017). Another approach is statistical downscaling, which combines historical observational data with large-scale patterns observed in the GCM output to create high resolution results at the scale of the observational data (Thrasher 2013; Hayhoe et al. 2017). One limitation of statistical downscaling is its dependence on large observational datasets, which are not available in every region, and its assumed statistical relationships (Hayhoe et al. 2017; Tommasi et al. 2017). Finally, empirical downscaling involves using a scaling factor to apply a projected change from a GCM to historical climate data time-series or model output (Ekström et al. 2015). Empirical downscaling is computationally inexpensive compared to dynamical and statistical downscaling (Tommasi et al. 2017), but it cannot represent interactions between large-scale and local changes and assumes the relationships between variables will not change in the future (Ramirez-Villegas and Jarvis 2010; Ekström et al. 2015). Overall, downscaling techniques produce finer-scale models that are relevant for making local resource management decisions (Thrasher 2013; Ekström et al. 2016). Downscaled climate change projections are particularly useful in region-specific studies regarding fisheries, protected species, and ecosystem modeling (Fulton et al. 2011; Grieve et al. 2016; Marshall et al. 2017; Olsen et al. 2018; Audzijonyte et al. 2019; Khangaonkar et al. 2019; Hollowed et al. 2020).

This study aims to quantify projected changes in Puget Sound ocean temperature and salinity under future climate change. We applied empirical downscaling techniques to derive high-resolution projections of future conditions in Puget Sound, based on scenario outputs of low-resolution GCMs from CMIP6. Our focus was on deriving downscaled projections for years 2020–2050 and 2070–2100 in Puget Sound. Data from this study will be used to drive an end-to-end ecosystem model of oceanography, food webs and human activities in Puget Sound, using the Atlantis modeling framework (Fulton et al. 2011; Audzijonyte et al. 2019), to help evaluate the effects of Southern Residents recovery actions and future threats (Morzaria-Luna et al. 2019, 2020a). This will allow for a rapid assessment of vulnerability of the Puget Sound ecosystem to climate change, as represented by this particular Atlantis model, building on the existing oceanography underlying this Atlantis implementation. By incorporating the latest CMIP6 results, this study complements past oceanographic projections using CMIP5, specifically Khangaonkar et al. (2019), which estimated an average ocean temperature increase of 1.51°C in the Salish Sea under a high emissions scenario (RCP8.5).

2 Methods

We developed downscaled projections for Sea Surface Temperature (SST) and sea surface salinity (Practical salinities, called salinity hereafter) in Puget Sound using the Delta Method (Ramirez-Villegas and Jarvis 2010). Anomalies were calculated from hindcast (1984-2014) and short-term (2020-2050) and long-term (2070-2100) forecast climatologies from the GFDL-CM4 (Held et al. 2019) and CNRM-CM6-1-HR (Voldoire et al. 2019) GCM model outputs. Next, we interpolated the anomalies using thin-plate spline interpolation and applied them to a temperature and salinity Regional Ocean Modeling System (ROMS) time series for 2005-2006 used to drive the Puget Sound Atlantis ecosystem model—a spatially-explicit, three dimensional model that integrates physical, chemical, ecological, and anthropogenic processes

using dynamic, two-way coupling (Fulton et al. 2011; Audzijonyte et al. 2019; Morzaria-Luna et al. 2020a). These time series were obtained by adjusting output from the high-resolution MoSSea model (Modeling the Salish Sea; MacCready 2018). All analyses were carried out using the R statistical framework (R Core Team 2020). All code is available in Github: https://github.com/steviewalker/Puget_Sound_Downscaling. Downscaled projections were deposited in the Knowledge Network for Biocomplexity data repository: https://knb.ecoinformatics.org/view/urn%3Auuid%3A02ff6032-59ea-4e30-8a96-65a02fe5ad04.

2.1 Study Area

Puget Sound is a large, complex estuarine system located in Washington State, USA, in the Northeast Pacific Ocean. It is part of the broader Salish Sea region, which also encompasses the Strait of Georgia and the Strait of Juan de Fuca. Within Puget Sound, there are four major basins: Hood Canal, Main Basin (Admiralty Inlet and Central Basin), South Basin, and Whidbey Basin (Encyclopedia of Puget Sound 2015). Many different habitats, home to a wide diversity of species, are found in Puget Sound, including saltmarshes, tidal flats, and eelgrass beds (Ruckelhaus and McClure 2007a; Reum et al. 2011; Khangaonkar et al. 2019). Puget Sound has the characteristics of a partially-mixed estuary, with river input mixing with strong, three- to four-meter tides (MacCready 2017). The Sound has an average water residence time of 90-180 days due to strong turbulent mixing by the tides (Sutherland et al. 2011). However, because of its relatively shallow sills, circulation and dispersal of water, sediment, organisms, and contaminants can be limited in some areas (Ruckelhaus and McClure 2007b; Andrews and Harvey 2013). Each basin has distinct physical differences due to bathymetry and differing amounts of saltwater and freshwater influence, and this complexity suggests that future conditions will involve an interplay of global trends superimposed on local, basin-specific characteristics. For example, waters in Hood Canal are highly stratified and marked by strong temperature and dissolved oxygen variations across depth, area, and season. It has a larger sea surface temperature range (~8-19 ℃) than other basins (MacCready 2020). In contrast, the Main Basin experiences seasonal temperature stratification with warmer surface waters in the summer (~14 ℃), due to river input and solar radiation, and a well-mixed, cooler water column in the winter (~8 ℃) due to reduced solar radiation and wind (Ruckelhaus and McClure 2007a; MacCready 2020). Across Puget Sound, there are seasonal variations in salinity, which are characteristic of coastal waters. During spring the water freshens and then salinity gradually increases as river runoff is mixed by the action of waves, winds, and tides; there are also early fall freshets rushes of fresh water flowing into the sea (Megia 1956). Average salinity in the Strait of San Juan de Fuca in the upper layer ranges from 30.7 in January to 31.6 in October, and in the bottom layer from 33.4 in February to 33.95 in August (Megia 1956). The Main Basin has an average surface salinity range of 26.5-29.0, while Hood Canal has an average surface salinity range of 21.0-26.5 (MacCready 2020). Salinities in the South Basin are higher than in the Main Basin; seasonal variation in salinity follows precipitation closely, with an average minimum of 28.4 in April to a maximum of 29.8 in November (Megia 1956).

2.2 CMIP6 and the ScenarioMIP

Results from 23 independently-led, CMIP-endorsed modeling projects will be used to inform international climate policy as part of the upcoming IPCC AR6 report (Eyring et al. 2016). CMIP6 builds upon climate modeling advances made in CMIP5 by introducing a new set of scenarios, including the Scenario Model Intercomparison Project (ScenarioMIP), which integrates future emission projections with societal concerns (Eyring et al. 2016; O'Neill et al. 2016). One key development within ScenarioMIP has been the development of five Shared Socioeconomic Pathways (SSPs), which are more developed scenarios to examine the interactions between physical climate change and global socioeconomic outcomes (Grose et al. 2020). SSPs describe possible trends in the development of society and ecosystems over the 21st century (O'Neill et al. 2014). The SSPs vary based on challenges to mitigation and adaptation society will face, and describe separate narratives: SSP1 - sustainability, SSP2 - middle of the road, SSP3 - regional rivalry, SSP4 - inequality, and SSP5 - fossil-fueled development (O'Neill et al. 2014; Riahi et al. 2017). In addition to SSPs, ScenarioMIP also includes different Representative Concentration Pathways (RCPs) which represent future physical outcomes of climate change and are based on the radiative forcing (W/m^2) in 2100 at the tropopause relative to preindustrial levels (O'Neill et al. 2016; Hayhoe et al. 2017). The RCPs were chosen to reflect different outcomes of land use and emission changes and are numbered based on the radiative forcing of each scenario: 1.9, 2.6, 3.4, 4.5, 6.0, 7.0, and 8.5. By combining different SSPs with different RCPs, ScenarioMIP produces eight projections (Fig. 2) that help address intermediate forcing levels and questions that fill in gaps from CMIP5 (Eyring et al. 2016; 2019; Meinshausen et al. 2019).

2.3 General Circulation Model Selection

Two GCMs were selected for data analysis: the NOAA Geophysical Fluid Dynamics Laboratory's CM4.0 physical climate model (GFDL-CM4; Held et al. 2019) and the Centre National de Recherches Météorologiques and Cerfacs' CNRM-CM6-1-HR physical climate model (Voldoire et al. 2019). Selection was based on CMIP6-endorsed models that participated in ScenarioMIP, had a high ocean grid resolution, and resolved some or all of the Salish Sea and Puget Sound. High ocean grid resolution was an important priority for the purpose of this project because it reduces uncertainty from interpolation (see section IV). All of the models evaluated are summarized in the supplemental material, however, only two met our criteria. The first model, GFDL-CM4, was built with the AM4.0/LM4.0 atmosphere/land model and OM4.0 ocean model (Held et al. 2019). OM4.0 has a newly updated ocean component (MOM6) with a nominal horizontal resolution of 0.25° (~25 km), which has led to many improvements in representing boundary currents in the global ocean, modeling ocean circulation, and more specifically, modeling regional currents (Adcroft et al. 2019; Held et al. 2019). GFDL-CM4 ran two scenarios from ScenarioMIP, ssp245 and ssp585. GFDL-CM4 resolves all parts of the Salish Sea, though at somewhat coarse 25-km resolution, including Puget Sound (Supplementary Material, Fig. S1). The GFDL-CM4 model simulations show a larger warming trend near the end of the historical runs as compared to observations; although the model shows low mean ocean temperature bias along the WA coast and nearby Eastern Pacific (Fig. S2; Rayner 2003). The second model, CNRM-CM6-1, was built using the atmosphere component ARPEGE-Climat version 6.3, the land component SURFEX version 8.0, and the ocean component NEMO version 3.6

(Gurvan et al. 2016; Voldoire et al. 2019). Unlike GFDL-CM4, the CNRM model focused on improving land and atmosphere components, whereas the ocean component has not been updated extensively from the CMIP5 model version (Voldoire et al. 2019). CNRM-CM6-1 ran scenarios ssp126, ssp245, ssp370, and ssp585 as part of CMIP6. The CNRM-CM6-1 model shows a low ocean warming bias along the WA coast and the Pacific Ocean (Fig. S2; Rayner 2003), but exhibits a warm bias between summer and fall (Voldoire et al. 2019). This model has a 25-km ocean grid resolution and spatially resolves much of the Salish Sea (e.g., the Strait of Juan de Fuca and Strait of Georgia), but not all of Puget Sound (Fig. S1). The upper water column in the GFDL model has a 2-m layer thickness near the surface, increasing to roughly 20 m at 200 m depth (Held et al. 2019), while the CNRM-CM6-1 model layer thickness increases from 1 m near the surface to 200 m at a depth of 6,000 m (Voldoire et al. 2019).

2.4 Empirical Downscaling

The Delta Method (Ramirez-Villegas and Jarvis 2010; Jones 2013; Ekström et al. 2015) is a relatively straightforward approach to GCM downscaling that is used to produce high-resolution seasonal climatologies for a region (Silva et al. 2015). It involves calculating interpolated anomalies of monthly time series climatologies from the GCM relative to a model hindcast (Jones 2013; Silva et al. 2015; Ekström et al. 2015). In order to do this, we first obtained hindcasts and forecasts from two CMIP-endorsed GCMs, CNRM-CM6-1-HR and GFDL-CM4, for our two focus variables: SST and salinity. These focus variables were chosen because they are two key physical variables that impact circulation and biological processes, they will both be impacted by climate change, and they will be used to force the Atlantis ecosystem model for Puget Sound (Morzaria-Luna et al. 2020b). Available data on each CMIP6 model and scenario were obtained from the Earth System Grid Federation data repository (https://esgf-node.llnl.gov/search/cmip6/), using the ESGF Search RESTful API (https://earthsystemcog.org/projects/cog/esgf_search_restful_api). We standardized the data and calculated running monthly SST and salinity climatologies for a 30-year hindcast period (1984-2014), short-term forecast period (2020-2050), and long-term forecast period (2070-2100) based on the different scenarios from CMIP6 (Eyring et al. 2016; O'Neill et al. 2016). Anomalies were then calculated from the absolute difference between forecasts and hindcast climatologies for both variables in each scenario from each GCM. We interpolated the anomalies using the centroids of GCM cells as points of interpolation and applied thin plate spline (TPS) interpolation across these points to obtain anomalies at higher resolutions (3 and 0.1 km), such that these anomalies could then be mapped onto the high-resolution ROMS model, as detailed below.

2.5 Salish Sea ROMS and the Atlantis ecosystem model

After interpolation, the 0.1-km resolution anomalies were applied to the ocean temperature and salinity time series that drive the Atlantis model for Puget Sound. Atlantis is a spatially-explicit marine and coastal modeling framework that integrates biophysical, chemical, ecological, and fisheries dynamics in a three-dimensional domain represented by an irregular polygon structure (Fulton et al. 2011). Atlantis simulates the food web and fisheries and is designed to produce realistic simulations of ecosystem

dynamics and allow exploration of ecosystem responses under different ecological, management, or impact scenarios (Nilsen 2018). The Atlantis model for Puget Sound is driven by spatial and temporal fields of circulation, temperature, and salinity that are based on output from a high-resolution realistic numerical simulation of the Salish Sea referred to as MoSSea (Modeling the Salish Sea; Sutherland et al. 2011). MoSSea is based on the Regional Ocean Modeling System (ROMS) numerical framework, which solves hydrostatic, incompressible, Reynolds-averaged momentum and tracer conservation equations with a terrain-following vertical coordinate and a free surface (Haidvogel et al. 2000; Shchepetkin and McWilliams 2005). The MoSSea model's horizontal domain is a spherical, stretched Cartesian grid extending from longitude -127° to -122°, and latitude 45° to 50° N. The grid resolution is as fine as 280 m and stretches to 3.1 km at the boundaries; there are 20 vertical layers. This model was forced with measured flow from 16 rivers, tides, atmospheric forcing by wind stress and heat flux, and open ocean boundary conditions. When validating the MoSSea model against observed temperature and salinity CTD casts, it was found that the model captured the seasonal cycles of SST and salinity well, showing positive skill scores and significant positive correlations with 7 out of 8 CTD stations' observations of surface salinity and surface temperature (Sutherland et al. 2011). MoSSea showed the most discrepancies between modeled and observed data in Hood Canal, which is difficult to model because it is the narrowest and deepest part of Puget Sound (Sutherland et al. 2011). Overall MoSSea was about 0.5 units saltier than observations (Sutherland et al. 2011). The MoSSea was run for the years 2005 and 2006, with the initial fields in Puget Sound for each year extrapolated from available CTD cast observations. These years were chosen for the model run because of optimal overlap with observations on the coastal shelf. The choice of years is arbitrary, as the two-year period is meant to capture the seasonal cycle in Puget Sound, and the Delta Method we applied is adding a time-step increase to the MoSSea 2005-2006 baseline output. In order to adapt the regular-shaped MoSSea grid to the irregular Atlantis spatial polygons, fields were averaged at 12-hour time steps, and oceanography for each Atlantis polygon was interpolated to the nearest velocity grid point on the MoSSea grid. For application in this paper, we superimposed the anomalies onto the time series for each Puget Sound Atlantis model polygon.

3 Results

We first calculated interpolated anomalies downscaled at 3-km resolution for the entire Salish Sea and surrounding regional waters (Fig. 3, Fig. S3, and Fig. S4). There was an increase in SST between the short-term (2020-2050) and long-term (2070-2100) projections, under every scenario and for both models. The CNRM-CM6-1-HR model predicted a lower SST anomaly overall than the GFDL-CM4 model. The spatial patterns of SST change were relatively consistent between the two models; slightly higher anomalies were found within the Strait of Georgia and Puget Sound for any given scenario (Fig. S3). These spatial differences were more pronounced in the long-term high emissions scenario ssp585. For the SST interpolated anomaly projections, the GFDL-CM4 model had slightly warmer projections than the CNRM-CM6-1-HR model, with a maximum SST anomaly of 4.67℃ (long-term ssp585 projection scenario) and a minimum SST anomaly of 0.85℃ (short-term ssp245 projection scenario). The SST

anomaly for CNRM-CM6-1-HR ranged between a maximum of 3.96℃ (long-term ssp585 projection scenario), and a minimum SST anomaly of 0.52℃ (short-term ssp245 projection scenario).

Salinity projections, across all models and scenarios, showed increased freshening of the Salish Sea in the long-term (Fig. 3, Fig. S4). However, the magnitude of freshening differs between models; the CNRM-CM6-1-HR model predicts greater freshening than the GFDL-CM4 model. Furthermore, there were differences in the spatial pattern between the models as well. The GDL-CM4 model showed a less negative salinity anomaly, and in some cases, a positive salinity anomaly around the mouth of the Columbia River, in South Puget Sound, and in the Northern Strait of Georgia (Fig. 3). In contrast, for CNRM-CM6-1-HR, the Salish Sea as a whole had a more negative salinity anomaly than the Pacific Ocean, with slightly less negative anomalies in South Puget Sound only in some projections (Fig. S4). Across the spatial domain, the salinity anomaly for the GFDL-CM4 model ranged between a maximum of 0.83 salinity units (short-term ssp585 projection) and a minimum of -0.60 (long-term ssp585 projection). For CNRM-CM6-1-HR, there was a wider range in the salinity anomaly across the spatial domain: a maximum salinity anomaly of 0.17 for the short-term ssp370 projection, and a minimum salinity anomaly of -2.16 for the long-term ssp585 projection.

The interpolated regional anomalies were then applied to the ROMS time series for Puget Sound (MoSSea, MacCready 2018), and these high-resolution (0.1 km) downscaled results showed variations between scenarios for each model. The seasonal patterns come from the 2005-2006 ROMS time series, shown as a black baseline in Fig. 4 and Fig. 5. The final downscaled results reflect the high-resolution patterns in the ROMS and the step increase from the CMIP6 interpolated anomaly. For SST, this reflects seasonal changes in solar insolation, with the warmest temperatures found in the summer and the coldest in the winter (Fig. 4). For salinity, the jagged pattern is due to seasonal and annual changes in snowmelt and precipitation, with rapid decreases in salinity during the rainy winter months and during the spring snowmelt, and a slow steady increase during the drier summer months (Fig. 5).

Applying the interpolated anomalies over the ROMS time-series data allows us to predict actual temperature and salinity values at a fine spatial scale, as opposed to the anomaly results discussed previously. In both short-term and long-term projections and for every downscaled scenario, SST is projected to increase (Fig. 4). SST changes are higher in the long-term projections (maximum average SST = 19.6℃, minimum average SST = 8.7℃, Table S2) compared to the short-term projections (maximum average SST = 16.5℃, minimum average = 8.0℃, Table S2). Here, the maxima and minima refer to averages over all Puget Sound Atlantis ecosystem model spatial polygons. The average downscaled SST increase from the ROMS baseline for the long-term ssp585 projection is 3.5℃ for the CNRM-CM6-1-HR model and 3.9℃ for the GFDL-CM4 model (Table S2). The intensity of SST warming increases from the lowest emissions scenario, ssp126, to the highest emissions scenario, ssp585.

Both models predict a decrease in salinity in the long-term for every scenario (Fig. 5). In the short-term, the CNRM-CM6-1-HR model predicted a decrease in salinity, while the GFDL-CM4 model predicted a slight increase in salinity. Freshening was greater in the long-term for both models (maximum average salinity =

30.9, minimum average salinity = 25.2, Table S2) compared to the short-term (maximum average salinity = 31.4, minimum average salinity = 26.5, Table S2). As with SST maxima and minima, the minimum and maximum average salinity refers to the average over all spatial polygons. The average downscaled salinity decrease from the ROMS baseline for the long-term ssp585 projection is -1.9 for the CNRM-CM6-1-HR model and -0.5 for the GFDL-CM4 model (Table S2). Intensity of freshening is more pronounced at higher emissions scenarios than at lower emissions scenarios. Variability in both SST and salinity change is greater in the long-term projections because there is less certainty in the GCMs about projected outcomes further in the future.

Only scenarios ssp245 and ssp585 can be compared between both models, because as previously noted, GFDL-CM4 did not run scenarios ssp126 and ssp370. Overall, the GFDL-CM4 model results were slightly warmer and saltier than the CNRM-CM6-1-HR model results (Fig. 6). Salinity results showed more inter-model variation than SST. In other words, the two models had very high agreement for SST results, but salinity, while highly correlated between models, was greater in the GFDL-CM4 model than in CNRM-CM6-1-HR. There is greater range in salinity in the long-term compared with the short-term (Fig. 6), which is likely an outcome of model configuration differences between the GFDL-CM4 model and the CNRM-CM6-1-HR model.

Final downscaled results overlaid onto the ROMS data showed basin-specific spatial differences within Puget Sound. Overall, the highest average projected SSTs were found within Hood Canal and South Basin, while the lowest projected SSTs were found within the Eastern Strait of Juan de Fuca (Fig. 7). The projected freshest waters were found near areas of major river input, mainly the Snohomish and Skagit Rivers in the Whidbey basin (Fig. 7). Projected salinity was higher near the Strait of Juan de Fuca and the Strait of Georgia (Fig. 7). The degree of freshening and warming increased from the short-term to the long-term projections for each scenario, and the most severe projected freshening and warming occurred at higher-emissions scenarios in the long-term (Fig. S6 and Fig. S7).

4 Discussion

We developed short-term (2020-2050) and long-term (2070-2100) downscaled projections for SST and salinity in Puget Sound, using two GCM models, CNRM-CM6-1-HR model and GFDL-CM4. Over the 21st century, both models predict warming and freshening of Puget Sound. This general result is in-line with the Puget-Sound-specific findings in Khangaonkar et al. (2019) and the broader findings in the California Current (Xiu et al. 2018; Siedlecki et al. 2020). Warming and freshening is greater in the long-term than in the short-term. The severity of these effects is dependent on the CMIP6 emissions scenario. In ssp585, representing a fossil-fuel dependent, high emissions world, there will be greater warming and freshening than in ssp126, which represents a sustainable, low-emissions world (Riahi et al. 2017). The CNRM-CM6-1-HR model and the GFDL-CM4 model have strong agreement on SST increases and less agreement on salinity. Spatially, the projected SST increase in Puget Sound is the greatest in Hood Canal and South Basin, and the projected salinity decrease is the greatest in Main Basin.

The models differed in their predictions of future anomalies, though more in terms of salinity than SST. The GFDL-CM4 model had slightly warmer predictions compared to the CNRM-CM6-1-HR model, up to 0.4 °C greater (Table S2). Salinity patterns were more varied than SST, with the GFDL-CM4 model showing a slight increase in salinity in the short-term and the CNRM-CM6-1-HR showing greater long-term freshening, up to 1.4 units fresher (Table S2). This distinction between models does not mean one is necessarily more accurate than the other; it is likely a result of different ocean model component configurations. The CNRM-CM6-1-HR model uses the NOCS-ORCA1 configuration of the ocean model NEMO version 3.6 (Danabasoglu et al. 2014; Voldoire et al. 2019), and the GFDL-CM4 model uses the MOM6 configuration of OM4.0 (Adcroft et al. 2019; Held et al. 2019). The different parameterizations used in the GCMs could account for different model responses to the same forcing, as in the case of salinity (Zelinka et al. 2020; Brunner et al. 2020). Internal variability and potential biases in GCMs can be exacerbated at regional scales (Lehner et al. 2020; Brunner et al. 2020). Including additional models to expand a multi-model comparison would have helped understand how choice of GCM influences model predictions due to uncertainty in different model parameterizations (Tommasi et al. 2017). However, choosing the GCM that resolved Puget Sound with the best spatial resolution was more important for the purpose of this project in order to reduce uncertainty from interpolating. The GDFL-CM4 model and the CNRM-CM6-1-HR model were the only two models we found that spatially resolved part or all of the Salish Sea on their horizontal grid, participated in ScenarioMIP, and had the data needed available for download (Table S1).

Each scenario resulted in different SST and salinity anomalies for Puget Sound, and the anomalies increased from the low emissions scenario ssp126 up to the high emissions scenario ssp585. Within the ScenarioMIP framework, scenarios have been updated relative to CMIP5 to include both the Representative Concentration Pathways (RCPs) of radiative forcing (W/m^2), and new Shared Socioeconomic Pathways (SSPs) that identify different societal outcomes over the 21st century (Fig. 2, O'Neill et al. 2014; Riahi et al. 2017). For the four different scenarios used in this study, ssp126 represents the most sustainable development, lowest emissions, reduced socioeconomic and political inequality, and the most reduced climate change impacts (Riahi et al. 2017). This scenario also coincides with the least amount of freshening and warming in Puget Sound. ssp245 is an intermediate scenario, where progress towards reducing emissions, protecting environmental systems, and reducing global inequality is achieved more slowly (Riahi et al. 2017). Intuitively, increases in SST and salinity are slightly greater in ssp245 than in ssp126. Nationalism dominates in ssp370, resulting in vast regional differences in the reduction of emissions, quality of life, and environmental degradation (Riahi et al. 2017). Thus, warming and freshening in Puget Sound intensifies even more than in ssp245. The greatest amount of warming and freshening in Puget Sound is predicted for ssp585, the business-as-usual scenario in which fossil-fuel reliant development occurs and energy intensive lifestyles become globally widespread (Riahi et al. 2017). The range of outcomes for Puget Sound are dependent upon which scenario the world follows over the 21st century.

The spatial differences in Fig. 7 are primarily generated from the MoSSea ROMS model (Sutherland et al. 2011), which simulates circulation in the Salish Sea. The warmest regions of downscaled projected SST, Hood Canal and South Basin (Fig. 1 and Fig. 7), are both connected to the Main Basin by narrow passages that are constrained in part by shallow sills. Surface warming in these regions is likely greater due to a more constricted water flow and a narrower topography. SST changes are less extreme in the northern basins, where there is strong tidal inflow from the Strait of Juan de Fuca into Puget Sound (~16000 m^3s^{-1}) (Khangaonkar et al. 2019). The freshening seen in the final interpolated values (Fig. 7) is greatest near areas of major river input, such as the Whidbey Basin, where the Skagit and Snohomish rivers have an average discharge of ~1000 m^3s^{-1} (Sutherland et al. 2011). However, because in Puget Sound the tidal influence is stronger than river input, the effects of river discharge on salinity are only noticeable in regions nearest to river mouths. The average downscaled results echo the interpolated anomalies from the CMIP6 results because the Delta Method is adding a step increase to the ROMS time series. Imposing the anomalies to the ROMS time series allows us to see seasonal differences, as forced by the ROMS, and obtain high-resolution values for SST and salinity that are more useful to further ecosystem-based management applications, such as the Puget Sound Atlantis ecosystem model development (Morzaria-Luna et al. 2020b), than anomalies alone.

Patterns of warming ocean temperatures and freshening waters are driven by atmospheric and terrestrial conditions, which are also changing as a result of climate change. Globally, average atmospheric temperature has already increased 1℃ from pre-industrial levels, and future warming of 1.5℃ in Washington State is expected to lead to a 67% increase in hot days above 32℃, a 38% decrease in snowpack, and a 16% increase in winter streamflow (Snover et al. 2019). Precipitation conditions are expected to shift towards a rain-dominated watershed and are likely to be slightly wetter overall, but with 20-27% drier summers in the long term and increasing frequency of heavy precipitation events (Mauger et al. 2015). Alterations in streamflow and the amount of precipitation drive salinity changes in Puget Sound (Moore et al. 2015). Melting glaciers in the North Cascades and Olympic mountain ranges, as well as earlier spring streamflow, will shift the amount and timing of river input. Additionally, warming surface waters have the potential to increase stratification, which with overall freshening in Puget Sound, could cause changes in mixing; it is unknown how much salinity variations will affect stratification and mixing (Yang and Khangaonkar 2008; Mauger et al. 2015).

The empirical downscaling methodology used in this paper is an important first step to developing CMIP6 climate projections for Puget Sound until a more detailed dynamical downscaling, similar to the methodology used for the Salish Sea by Khangaonkar et al. (2019) for CMIP5, can be carried out. For the purpose of ecosystem assessment, conservation planning, and other regional applications, empirical downscaling provides a method of rapid climate assessment with high climate realism (Ramirez-Villegas and Jarvis 2010; Ekström et al. 2015). However, it is important to remember that empirical downscaling does not make GCM output more accurate or reliable (Jones 2013), which is why we chose to use models that resolved Puget Sound with the highest initial resolution available (25 km; Fig. S3). One limitation of empirical downscaling is that it cannot account for changes in variability on the local scale because in

empirical downscaling, the climate signal is coming from the coarse resolution GCM (Ekström et al. 2015). Regional feedbacks, such as local precipitation changes or circulation changes, are not well-simulated by the GCM; this is another source of error (Mearns et al. 2003; Ekström et al. 2015). Furthermore, empirical downscaling assumes that the anomaly patterns will hold true in the future (Ramirez-Villegas and Jarvis 2010), which may not be the case for Puget Sound. Though we provide both short-term and long-term projections, we expect uncertainty to be higher in the long-term projections, though at this time scale the choice of downscaling method may be less critical. In particular, categorizing uncertainty in terms of scenario uncertainty, model uncertainty, and internal variability (Cheung et al. 2016), we expect scenario uncertainty to increase and dominate over the long-term - in other words, the global decisions about emissions become stronger drivers of predicted ocean conditions than decisions about GCMs and downscaling technique. Overall, empirical downscaling was chosen for the purpose of rapid, straightforward assessment, but dynamical downscaling for Puget Sound using CMIP6 models will be an important next step in developing more accurate SST and salinity predictions.

Improving accuracy in SST and salinity projections will be important in the coming decades because it will allow better evaluation of the ecosystem impacts of climate change in Puget Sound. In particular, understanding how climate change will affect all trophic levels and culturally significant species such as Chinook salmon, Pacific herring (*Clupea pallasii*), and Southern Residents is of key relevance to Puget Sound. Both Southern Residents and Puget Sound Chinook salmon are listed under the Endangered Species Act (as endangered and threatened, respectively), and Pacific herring are a critical forage species for salmon and protected seabirds and marine mammals. Increased ocean temperatures can be harmful to salmon during multiple stages of their life cycle, impacting spawning and migration, increasing mortality, and the risk of pathogens (Battin et al. 2007; Beauchamp and Duffy 2011; Mauger et al. 2015). Higher ocean temperatures could also lead to higher Pacific herring embryo mortality (Villalobos et al. 2020). Furthermore, the loss in snowpack will reduce salmon spawning area in rivers in the Puget Sound watershed, leading to an expected decline in salmon population (Battin et al. 2007). This has been identified as the highest Puget Sound salmon exposure risk (Crozier et al. 2019). Freshening and warming has the potential to lead to more stratification in Puget Sound, which directly affects primary production through a changing nutrient supply (Mauger et al. 2015; Xiu et al. 2018). Warming will also continue to change phytoplankton dynamics in Puget Sound, leading to increased harmful algal blooms, which can be toxic to fish (Moore et al. 2015; Southern Resident Orca Task Force 2019). The fate of Southern Resident orcas is fundamentally tied to Chinook salmon, the orca's primary food source (Ford et al. 2010). Compounding ecosystem stressors may have rippling effects at every trophic level, potentially leading to largely reduced food resources for the Southern Residents (Southern Resident Orca Task Force 2019). Climate change will increase ecosystem vulnerability to other anthropogenic impacts, emerging from a 42% human population increase expected by 2050 (Puget Sound Regional Council 2019).

We produced downscaled anomalies for the whole Salish Sea and downscaled time series for Puget Sound. Downscaled anomalies can be used to assess changes in species distributions (Petatán-Ramírez et al. 2019), and to guide resource-specific, basin-specific, or ecosystem-scale climate adaptation and resilience strategies, which is an emerging priority for the Puget Sound Partnership, the State of

Washington agency tasked with recovery of Puget Sound habitats, resources and services (Puget Sound Partnership 2018). The downscaled time series also will be used to drive scenarios using the Atlantis model for Puget Sound, a deterministic simulation model designed to support strategic decision making for marine resource management (Weijerman 2017). Within Atlantis, temperature directly affects primary production, respiration, and other metabolic processes, and both temperature and salinity can dictate habitat use (Audzijonyte et al. 2019). Therefore, downscaled ocean projections will directly influence simulated growth of individuals, population dynamics, and spatial and trophic relationships of species ranging from phytoplankton to fish and marine mammals (Fulton 2001). Initially, the downscaled time series derived here will be used to link scenarios of warming oceanography to Atlantis simulations that test to what extent 'speeding up' ecosystem-wide anabolic processes (e.g., gains due to higher growth rates) will be balanced by 'speeding up' catabolic processes (e.g., losses due to declines in assimilation rates or increases in predation mortality). Higher trophic level species including Southern Residents and salmon within Atlantis are affected both by their own direct physiological responses to temperature, and to the temperature-driven responses of the forage base. Results from Atlantis ecosystem model simulations will help inform recommendations for ecosystem-based management (EBM) in Puget Sound (Hamel et al. 2017), particularly when it comes to evaluating how climate change, management decisions, ecological changes, and other influences will effect Chinook salmon populations, as well as the population of one of their key predators: the endangered Southern Residents orcas (Morzaria-Luna et al. 2019, 2020a). Other Atlantis ecosystem modeling projects have used downscaled projections from GCMs to drive their models, such as the Benguela and Agulhas Currents Atlantis model (Ortega-Cisneros et al. 2018), California Current Atlantis model (Marshall et al. 2017), and the Nordic and Barents Sea Atlantis model (Hansen et al. 2019). Empirical downscaling is an effective way to obtain finer spatial scale resolutions needed for making ecosystem level analysis.

5 Concluding Remarks

Overall, warming SST and freshening are expected to intensify the most in the long-term high emissions scenarios (ssp585), where climate change impacts from a fossil fuel intensive economy are the greatest. The downscaled projections show agreement between the GFDL-CM4 model and CNRM-CM6-1-HR model, but there is more variability for salinity. These SST and salinity changes are driven by warming atmospheric temperatures and shifts in precipitation patterns in Washington State. Warming ocean temperatures are already causing dynamic shifts at all levels of the food web, particularly an increase in harmful algal blooms (Moore et al. 2015), reduction in survival for threatened Chinook salmon (Crozier et al. 2019), and increasing starvation risk for the endangered Southern Residents (Southern Resident Orca Task Force 2019). Because density is dominated by salinity relative to temperature, circulation in Puget Sound does not appear to be affected by warming ocean temperatures (Khangaonkar et al. 2019). Understanding how ocean conditions will vary based on CMIP6 climate change scenarios is critical for evaluating the intensity of change in Puget Sound, within individual basins and in the ecosystem as a whole. With high-resolution downscaled SST and salinity projections, we will be able to more accurately model ecosystem conditions using the Puget Sound Atlantis ecosystem model (Morzaria-Luna et al.

2020a) and complete rapid assessments of EBM decisions. Incremental improvements in climate downscaling will support informed policy decisions and conservation recommendations that will be critical for informing the vital signs of Puget Sound (Puget Sound Partnership 2019) and understanding the interconnectedness of all aspects of the ecosystem and climate change related threats.

Declarations

Acknowledgements

This work was funded by the WA SeaGrant project “Evaluating the effects of Southern Resident orcas recovery actions and external threats in the marine ecosystem of Puget Sound” and by the NOAA Ernest F. Hollings Undergraduate Scholarship Program. Computing resources were funded by the Microsoft Azure AI for Earth grant. We would like to thank Chris Harvey for reviewing a previous version of the document. Manuel Dorantes assisted with correcting the references.

I. Funding: Funding for this research comes from the Washington State Sea Grant “Evaluating the effects of Southern Resident orcas recovery actions and external threats in the marine ecosystem of Puget Sound”, the Microsoft AI for Earth Grant, and the NOAA Ernest F. Hollings Scholarship Program.

II. Conflicts of interest/competing interests: The authors have no conflicting interests to declare.

III. Availability of data: Downscaled climate projections are available in the following Knowledge Network for Biocomplexity data repository: https://knb.ecoinformatics.org/view/urn%3Auuid%3A02ff6032-59ea-4e30-8a96-65a02fe5ad04

IV. Code availability: All code is available in the following Github repository: https://github.com/steviewalker/Puget_Sound_Downscaling

V. Authors’ contributions: Conceptualization: Stevie Walker, Hem Nalini Morzaria-Luna, Isaac Kaplan; Methodology: Stevie Walker, Hem Nalini Morzaria-Luna, Isaac Kaplan, David Petatán-Ramírez; Code: Stevie Walker, Hem Nalini Morzaria-Luna, David Petatán-Ramírez; Formal analysis and investigation: Stevie Walker, Hem Nalini Morzaria-Luna; Writing - original draft preparation: Stevie Walker; Writing - review and editing: Stevie Walker, Hem Nalini Morzaria-Luna, Isaac Kaplan, David Petatán-Ramírez; Funding acquisition: Hem Nalini Morzaria-Luna, Isaac Kaplan; Resources: Hem Nalini Morzaria-Luna; Supervision: Hem Nalini Morzaria-Luna, Isaac Kaplan; Visualization: Stevie Walker, Hem Nalini Morzaria-Luna

SW wrote the paper, revised the paper, performed the data analysis, and developed the figures. HNML conceived and designed the analysis, performed the data analysis, helped acquire project funding, and revised the paper. IK revised the paper, conceived and designed the analysis, and helped acquire project funding. DPR provided code for the analysis and revised the paper.

VI. Ethics approval: The authors state no conflict of interest.

VII. Consent to participate: All authors have reviewed and have accepted the final version of the document.

References

1. Adcroft A, Anderson W, Balaji V et al (2019) The GFDL Global Ocean and Sea Ice Model OM4.0: Model Description and Simulation Features. J Adv Model Earth Syst 11:3167–3211. https://doi.org/10.1029/2019MS001726
2. Andrews KS, Harvey CJ (2013) Ecosystem-level consequences of movement: seasonal variation in the trophic impact of a top predator. Mar Ecol Prog Ser 473:247–260. https://doi.org/10.3354/meps10095
3. Audzijonyte A, Pethybridge H, Porobic J, Gorton R, Kaplan I, Fulton EA (2019) Atlantis: A spatially explicit end-to-end marine ecosystem model with dynamically integrated physics, ecology and socio-economic modules. Methods Ecol Evol 10:1814–1819. https://doi.org/10.1111/2041-210X.13272
4. Battin J, Wiley MW, Ruckelshaus MH, Palmer RN, Korb E, Bartz KK, Imaki K (2007) Projected impacts of climate change on salmon habitat restoration. PNAS 104:6720–6725. https://doi.org/10.1073/pnas.0701685104
5. Beauchamp DA, Duffy EJ (2011) Stage-specific growth and survival during early marine life of Puget Sound Chinook salmon in the context of temporal-spatial environmental conditions and trophic interactions. Washington Cooperative Fish and Wildlife Research Unit
6. Bianucci L, Long W, Khangaonkar T, Pelletier G, Ahmed A, Mohamedali T, Roberts M, Figueroa-Kaminsky C (2018) Sensitivity of the regional ocean acidification and carbonate system in Puget Sound to ocean and freshwater inputs. Elem Sci Anth 6:22. https://doi.org/10.1525/elementa.151
7. Blackmore L, Mitchell A, Cochrane C et al (2019) State of the Sound Report. Puget Sound Partnership
8. Bopp L, Resplandy L, Orr JC, Doney SC, Dunne JP, Gehlen M, Halloran P, Heinze C, Ilyina T, Séférian R, Tijputra 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
9. Brunner L, Pendergrass AG, Lehner F, Merrifield AL, Lorenz R, Knutti R (2020) Reduced global warming from CMIP6 projections when weighting models by performance and independence. Earth System Dynamics
10. Busch DS, McElhany P (2016) Estimates of the Direct Effect of Seawater pH on the Survival Rate of Species Groups in the California Current Ecosystem. PLoS One 11:e0160669. https://doi.org/10.1371/journal.pone.0160669
11. Cheung WWL, Frölicher TL, Asch RG, Jones MC, Pinsky ML, Reygondeau G, ROdgers KB, Rykaczewski RR, Sarmiento JL, Stock C, Watson JR (2016) Building confidence in projections of the responses of living marine resources to climate change. ICES J Mar Sci 73:1283–1296. https://doi.org/10.1093/icesjms/fsv250

12. Colby JM (2018) Orca: How We Came to Know and Love the Ocean's Greatest Predator. J Mammal 100:261–265. https://doi.org/10.1093/jmammal/gyy152
13. Crozier LG, McClure MM, Beechie T et al (2019) Climate vulnerability assessment for Pacific salmon and steelhead in the California Current Large Marine Ecosystem. PLoS One 14:e0217711. https://doi.org/10.1371/journal.pone.0217711
14. Daly EA, Brodeur RD (2015) Warming Ocean Conditions Relate to Increased Trophic Requirements of Threatened and Endangered Salmon. PLoS One 10:e0144066. https://doi.org/10.1371/journal.pone.0144066
15. Danabasoglu G, Yeager SG, Bailey D et al (2014) North Atlantic simulations in Coordinated Ocean-ice Reference Experiments phase II (CORE-II). Part I: Mean states. Ocean Model 73:76–107. https://doi.org/10.1016/j.ocemod.2013.10.005
16. Daron J, Macadam I, Kanamaru H, Cinco T, Katzfey J, Scannell C, Jones R, Li MV, Cruz F, Narisma G, Delfino RJ, Lasco R, Manalo J, Ares E, Solis AL, de Guzman R, Basconcillo J, Targang F (2018) Providing future climate projections using multiple models and methods: insights from the Philippines. Clim Change 148:187–203. https://doi.org/10.1007/s10584-018-2183-5
17. Doney SC, Fabry VJ, Feely RA, Kleypas JA (2009) Ocean acidification: the other CO_2 problem. Ann Rev Mar Sci 1:169–192. https://doi.org/10.1146/annurev.marine.010908.163834
18. Doney SC, Ruckelshaus M, Duffy JE, Barry JP, Chan F, English CA, Galindo HM, Grebmeier JM, Hollowed AB, Knowlton N, Polovina J, Rabalais NN, Sydeman WJ, Talley LD (2012) Climate change impacts on marine ecosystems. Ann Rev Mar Sci 4:11–37. https://doi.org/10.1146/annurev-marine-041911-111611
19. Ekström M, Grose MR, Whetton PH (2015) An appraisal of downscaling methods used in climate change research. WIREs Clim Change 6:301–319. https://doi.org/10.1002/wcc.339
20. Ekström M, Grose M, Heady C, Turner S, Teng J (2016) The method of producing climate change datasets impacts the resulting policy guidance and chance of mal-adaptation. Climate Services 4:13–29. https://doi.org/10.1016/j.cliser.2016.09.003
21. Encyclopedia of Puget Sound (2015) Geographic boundaries of Puget Sound and the Salish Sea. In: Encyclopedia of Puget Sound. https://www.eopugetsound.org/articles/geographic-boundaries-puget-sound-and-salish-sea. Accessed 12 Jun 2020
22. Eyring V, Bony S, Meehl GA, Senior CA, Stevens B, Stouffer RJ, Taylor KE (2016) Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization. Geosci Model Dev 9:1937–1958. https://doi.org/10.5194/gmd-9-1937-2016
23. Ford JKB, Ellis GM, Olesiuk PF, Balcomb KC (2010) Linking killer whale survival and prey abundance: food limitation in the oceans' apex predator? Biol Lett 6:139–142. https://doi.org/10.1098/rsbl.2009.0468
24. Fulton EA (2001) The effects of model structure and complexity on the behaviour and performance of marine ecosystem models. University of Tasmania

25. Fulton EA, Link JS, Kaplan IC, Savina-Rolland M, Johnson P, Ainsworth C, Horne P, Gorton R, Gamble RJ, Smith AD, Smith DC (2011) Lessons in modelling and management of marine ecosystems: the Atlantis experience. Fish Fish 12:171–188. https://doi.org/10.1111/j.1467-2979.2011.00412.x
26. Grieve BD, Curchitser EN, Rykaczewski RR (2016) Range expansion of the invasive lionfish in the Northwest Atlantic with climate change. Mar Ecol Prog Ser 546:225–237. https://doi.org/10.3354/meps11638
27. Grose MR, Narsey S, Delage FP et al (2020) Insights From CMIP6 for Australia's Future Climate. Earth's Future 8:e2019EF001469. https://doi.org/10.1029/2019EF001469
28. Gruber N (2011) Warming up, turning sour, losing breath: ocean biogeochemistry under global change. Phil Trans R Soc A 369:1980–1996. https://doi.org/10.1098/rsta.2011.0003
29. Gurvan M, Bourdallé-Badie R, Bouttier P-A et al (2016) NEMO ocean engine. Note du Pôle de modélisation de l'Institut Pierre-Simon Laplace
30. Haidvogel DB, Arango HG, Hedstrom K, Beckmann A, Malanotte-Rizzoli P, Shchepetkin AF (2000) Model evaluation experiments in the North Atlantic Basin: simulations in nonlinear terrain-following coordinates. Dyn Atmos Oceans 32:239–281. https://doi.org/10.1016/S0377-0265(00)00049-X
31. Hamel NJ, Joyce J, Fohn M, James A, Toft J, Lawver A, Redman S (2017) The 2015 State of the Sound: Report on the Puget Sound Vital Signs. Salish Sea Ecosystem Conference. cedar.wwu.edu
32. Hansen C, Nash RDM, Drinkwater KF, Hjøllo SS (2019) Management Scenarios Under Climate Change – A Study of the Nordic and Barents Seas. Frontiers in Marine Science 6:1–13. https://doi.org/10.3389/fmars.2019.00668
33. Hayhoe K, Edmonds J, Kopp R, LeGrande A, Sanderson B, Wehner M, Wuebbles D (2017) Climate models, scenarios, and projections. Publications, Agencies and Staff of the U.S. Department of Commerce, p 589. https://digitalcommons.unl.edu/usdeptcommercepub/589
34. Held IM, Guo H, Adcroft A, Dunne JP, Horowitz LW, Krasting J et al (2019) Structure and Performance of GFDL's CM4.0 Climate Model. J Adv Model Earth Syst 11:3691–3727. https://doi.org/10.1029/2019MS001829
35. Hollowed AB, Holsman KK, Haynie AC et al (2020) Integrated Modeling to Evaluate Climate Change Impacts on Coupled Social-Ecological Systems in Alaska. Front Mar Sci 6:1–18. https://doi.org/10.3389/fmars.2019.00775
36. Jones H (2013) Mechanistic Habitat Modeling with Multi-Model Climate Ensembles. Environmental Management, Duke University
37. Juckes M, Taylor KE, Durack PJ, Lawrence B, Mizielinski MS, Pamment A, Peterschmitt JY, Rixen M, Sénési S (2020) The CMIP6 Data Request (DREQ, version 01.00.31). Geosci Model Dev 13:201–224. https://doi.org/10.5194/gmd-13-201-2020
38. Keeling RE, Körtzinger A, Gruber N (2010) Ocean deoxygenation in a warming world. Ann Rev Mar Sci 2:199–229. https://doi.org/10.1146/annurev.marine.010908.163855
39. Khangaonkar T, Nugraha A, Xu W, Balaguru K (2019) Salish Sea Response to Global Climate Change, Sea Level Rise, and Future Nutrient Loads. J Geophys Res C: Oceans 124:3876–3904.

https://doi.org/10.1029/2018JC014670

40. Kroeker KJ, Kordas RL, Crim R, Hendriks IE, Ramajo L, Singh GS, Duarte CM, Gattuso JP (2013) Impacts of ocean acidification on marine organisms: quantifying sensitivities and interaction with warming. Glob Chang Biol 19:1884–1896. https://doi.org/10.1111/gcb.12179
41. Lehner F, Deser C, Maher N, Marotzke J, Fischer EM, Brunner L, Knutti R, Hawkins E (2020) Partitioning climate projection uncertainty with multiple large ensembles and CMIP5/6. Earth Syst Dyn 11:491–508. https://doi.org/10.5194/esd-11-491-2020
42. MacCready P (2017) Puget Sound's physical environment. In: Encyclopedia of Puget Sound. https://www.eopugetsound.org/articles/puget-sounds-physical-environment. Accessed 12 Jun 2020
43. MacCready P (2018) MoSSea: Modeling the Salish Sea. https://faculty.washington.edu/pmacc/Research/mossea.html. Accessed 18 Jun 2020
44. MacCready P (2020) Changes in Puget Sound Waters Over the Last Century. In: LiveOcean: Pacific Northwest Ocean and Estuary Forecasts. https://faculty.washington.edu/pmacc/LO/long_term_trends.html. Accessed 16 Jun 2020
45. Marshall KN, Kaplan IC, Hodgson EE, Hermann A, Busch DS, McElhany P, Essington TE, Harvey CJ, Fulton EA (2017) Risks of ocean acidification in the California Current food web and fisheries: ecosystem model projections. Glob Chang Biol 23:1525–1539. https://doi.org/10.1111/gcb.13594
46. Mauger GS, Casola JH, Morgan HA, Straunch RL, Jones B, Curry B, Busch Isaksen TM, Whitely Binder L, Krosby MB, Snover AK (2015) State of Knowledge: Climate Change in Puget Sound. Climate Impacts Group, University of Washington
47. Mearns LO, Giorgi F, Whetton P, Pabon D, Hulme M, Lal M (2003) Guidelines for Use of Climate Scenarios Developed from Regional Climate Model Experiments. IPCC
48. Megia TG (1956) The temperature and salinity characteristics of Puget Sound and Strait of Juan de Fuca based on the M. V. CATALYST observations of 1932 to 1942. Master's of Science, University of Washington
49. Meinshausen M, Nicholls ZRJ, Lewis J et al (2020) The shared socio-economic pathway (SSP) greenhouse gas concentrations and their extensions to 2500. Geosci Model Dev 13:3571–3605. https://doi.org/10.5194/gmd-13-3571-2020
50. Moore SK, Johnstone JA, Banas NS, Salathé EP Jr (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
51. Mora C, Wei C-L, Rollo A et al (2013) Biotic and human vulnerability to projected changes in ocean biogeochemistry over the 21st century. PLoS Biol 11:e1001682. https://doi.org/10.1371/journal.pbio.1001682
52. Morzaria-Luna HN, Schmidt M, Kaplan I, Fulton B, Pethybridge H, Porobic J, Knox M, Hall L (2019) Evaluating the effects of Southern Resident orcas recovery actions and external threats in the marine ecosystem of Puget Sound. Washington Sea Grant

53. Morzaria-Luna HN, Kaplan I, Harvey C, Girardin R, Fulton E, MacCready P, Chasco B, Horne P, Schmidt M (Unpublished report) Design and Parameterization of a Spatially Explicit Atlantis Ecosystem Model for Puget Sound. Northwest Fisheries Science Center
54. Nilsen I, Kolding J, Hansen C, Howell D (2020) Exploring Balanced Harvesting by Using an Atlantis Ecosystem Model for the Nordic and Barents Seas. Frontiers in Marine Science 7:70. https://doi.org/10.3389/fmars.2020.00070
55. Olsen E, Kaplan IC, Ainsworth C, Fay G, Gaichas S, Gamble R, Girardin R, Eide CH, Ihde TF, Morzaria-Luna HN, Johnson KF, Savina-Rolland M, Townsend H, Weijerman M, Fulton EA, Link JS (2018) Ocean Futures Under Ocean Acidification, Marine Protection, and Changing Fishing Pressures Explored Using a Worldwide Suite of Ecosystem Models. Front Mar Sci 5:1–23. https://doi.org/10.3389/fmars.2018.00064
56. O'Neill BC, Kriegler E, Riahi K, Ebi KL, Hallegatte S, Carter TR, Mathur R, van Vuuren DP (2014) A new scenario framework for climate change research: the concept of shared socioeconomic pathways. Clim Change 122:387–400. https://doi.org/10.1007/s10584-013-0905-2
57. O'Neill BC, Tebaldi C, van Vuuren DP, Eyring V, Friedlingstein P, Hurtt G, Knutti R, Kriegler E, Lamarque JF, Lowe J, Meehl GA, Moss R, Riahi K, Sanderson BM (2016) The Scenario Model Intercomparison Project (ScenarioMIP) for CMIP6. Geosci Model Dev 9:3461–3482. https://doi.org/10.5194/gmd-9-3461-2016
58. Ortega-Cisneros K, Cochrane KL, Fulton EA, Gorton R, Popova E (2018) Evaluating the effects of climate change in the southern Benguela upwelling system using the Atlantis modelling framework. Fish Oceanogr 27:489–503. https://doi.org/10.1111/fog.12268
59. Petatán-Ramírez D, Ojeda-Ruiz M, Sánchez-Velasco L, Rivas D, Reyes-Bonilla H, Cruz-Piñón G, Morzaria-Luna HN, Cisneros-Montemayor AM, Cheung W, Salvadeo C (2019) Potential changes in the distribution of suitable habitat for Pacific sardine (*Sardinops sagax*) under climate change scenarios. Deep Sea Res Part 2 Top Stud Oceanogr 169–170:104632. https://doi.org/10.1016/j.dsr2.2019.07.020
60. Popova E, Yool A, Byfield V, Cochrane K, Coward AC, Salim SS, Gasalla MA, Henson SA, Hobday AJ, Pecl GT, Sauer WH, Roberts MJ (2016) From global to regional and back again: common climate stressors of marine ecosystems relevant for adaptation across five ocean warming hotspots. Glob Chang Biol 22:2038–2053. https://doi.org/10.1111/gcb.13247
61. Puget Sound Partnership (2018) The 2018–2022 Action Agenda For Puget Sound. http://psp.wa.gov/action_agenda_center.php
62. Puget Sound Partnership (2019) State of the Sound Report. https://www.psp.wa.gov/sos.php
63. Puget Sound Regional Council (2019) Vision 2050. Draft Supplemental Environmental Impact Statement
64. R Core Team (2020) R: A language and environment for statistical computing. Version 3.6.3. R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/

65. Ramirez-Villegas J, Jarvis A (2010) Downscaling Global Circulation Model Outputs: The Delta Method Decision and Policy Analysis Working Paper No. 1. Consultative Group on International Agriculture Research
66. Rayner NA, Parker DE, Horton EB, Folland CK, Alexander LV, Rowell DP, Kent EC, Kaplan A (2003) Global analyses of sea surface temperature, sea ice, and night marine air temperature since the late nineteenth century. J Geophys Res 108.: https://doi.org/10.1029/2002jd002670
67. Reum JC, Esstington TE, Greene CM, Rice CA, Fresh KL (2011) Multiscale influence of climate on estuarine populations of forage fish: The role of coastal upwelling, freshwater flow and temperature. Mar Ecol Prog Ser 425:203–215. https://doi.org/10.3354/meps08997
68. Riahi K, van Vuuren DP, Kriegler E et al (2017) The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An overview. Glob Environ Change 42:153–168. https://doi.org/10.1016/j.gloenvcha.2016.05.009
69. Ruckelshaus M, McClure M (2007a) Sound Science: Synthesizing ecological and socioeconomic information about the Puget Sound ecosystem. National Oceanic and Atmospheric Administration - Northwest Fisheries Science Center
70. Ruckelhaus MH, McClure MM (2007b) Water and nutrient circulation in Puget Sound. In: Encyclopedia of Puget Sound. https://www.eopugetsound.org/articles/water-and-nutrient-circulation-puget-sound. Accessed 13 Sep 2021
71. Shchepetkin AF, McWilliams JC (2005) The regional oceanic modeling system (ROMS): a split-explicit, free-surface, topography-following-coordinate oceanic model. Ocean Model 9:347–404. https://doi.org/10.1016/j.ocemod.2004.08.002
72. Siedlecki SA, Pilcher D, Howard EM, Deutsch C, MacCready P, Norton EL, Newton J, Feely RA, Alin SR, Klinger T (2020) Coastal processes modify projections of some climate-driven stressors in the California Current System. Biogeosciences. http://doi.org/10.5194/bg-2020-279
73. Silva C, Yáñez E, Barbieri MA, Bernal C, Aranis A (2015) Forecasts of swordfish (*Xiphias gladius*) and common sardine (*Strangomera bentincki*) off Chile under the A2 IPCC climate change scenario. Prog Oceanogr 134:343–355. https://doi.org/10.1016/j.pocean.2015.03.004
74. Snover AK, Raymond CL, Roop HA, Morgan H (2019) No Time to Waste. The Intergovernmental Panel on Climate Change's Special Report on Global Warming of 1.5°C and Implications for Washington State. Climate Impacts Group, University of Washington
75. Southern Resident Orca Task Force (2019) Southern Resident Orca Task Force - Final Report and Recommendations. Cascadia Consulting Group
76. Stock CA, Alexander MA, Bond NA et al (2011) On the use of IPCC-class models to assess the impact of climate on Living Marine Resources. Prog Oceanogr 88:1–27. https://doi.org/10.1016/j.pocean.2010.09.001
77. Sutherland DA, MacCready P, Banas NS, Smedstad LF (2011) A Model Study of the Salish Sea Estuarine Circulation. J Phys Oceanogr 41:1125–1143. https://doi.org/10.1175/2011JPO4540.1

78. Tommasi D, Stock CA, Hobday AJ et al (2017) Managing living marine resources in a dynamic environment: The role of seasonal to decadal climate forecasts. Prog Oceanogr 152:15–49. https://doi.org/10.1016/j.pocean.2016.12.011
79. The CMIP6 landscape (2019) Nat Clim Chang 9:727. https://doi.org/10.1038/s41558-019-0599-1
80. Thrasher B, Xiong J, Wang W, Michaelis A (2013) Downscaled climate projections suitable for resource management. Eos 94:321–323
81. Villalobos C, Love BA, Olson MB (2020) Ocean Acidification and Ocean Warming Effects on Pacific Herring (*Clupea pallasi*) Early Life Stages. Front Mar Sci. https://doi.org/10.3389/fmars.2020.597899
82. Voldoire A, Saint-Martin D, Sénési S et al (2019) Evaluation of CMIP6 DECK Experiments With CNRM-CM6-1. J Adv Model Earth Syst 11:2177–2213. https://doi.org/10.1029/2019MS001683
83. Weijerman M (2017) Report of the Hawaii Atlantis Ecosystem Model Planning Workshop held in January 2017 in Honolulu. U.S. Department of Commerce, National Oceanic and Atmospheric Administration
84. Xiu P, Chai F, Curchitser EN, Castruccio FS (2018) Future changes in coastal upwelling ecosystems with global warming: The case of the California Current System. Sci Rep 8:1–9. https://doi.org/10.1038/s41598-018-21247-7
85. Yang Z, Khangaonkar T (2008) Modeling of Salt Intrusion, Intertidal Mixing, and Circulation in a Braided Estuary. J Coast Res 52.: https://doi.org/10.2112/1551-5036-52.sp1.171
86. Zelinka MD, Myers TA, McCoy DT, Po-Chedley S, Caldwell PM, Ceppi P, Klein SA, Taylor KE (2020) Causes of higher climate sensitivity in CMIP6 models. Geophys Res Lett 47:1–12. https://doi.org/10.1029/2019gl085782

Figures

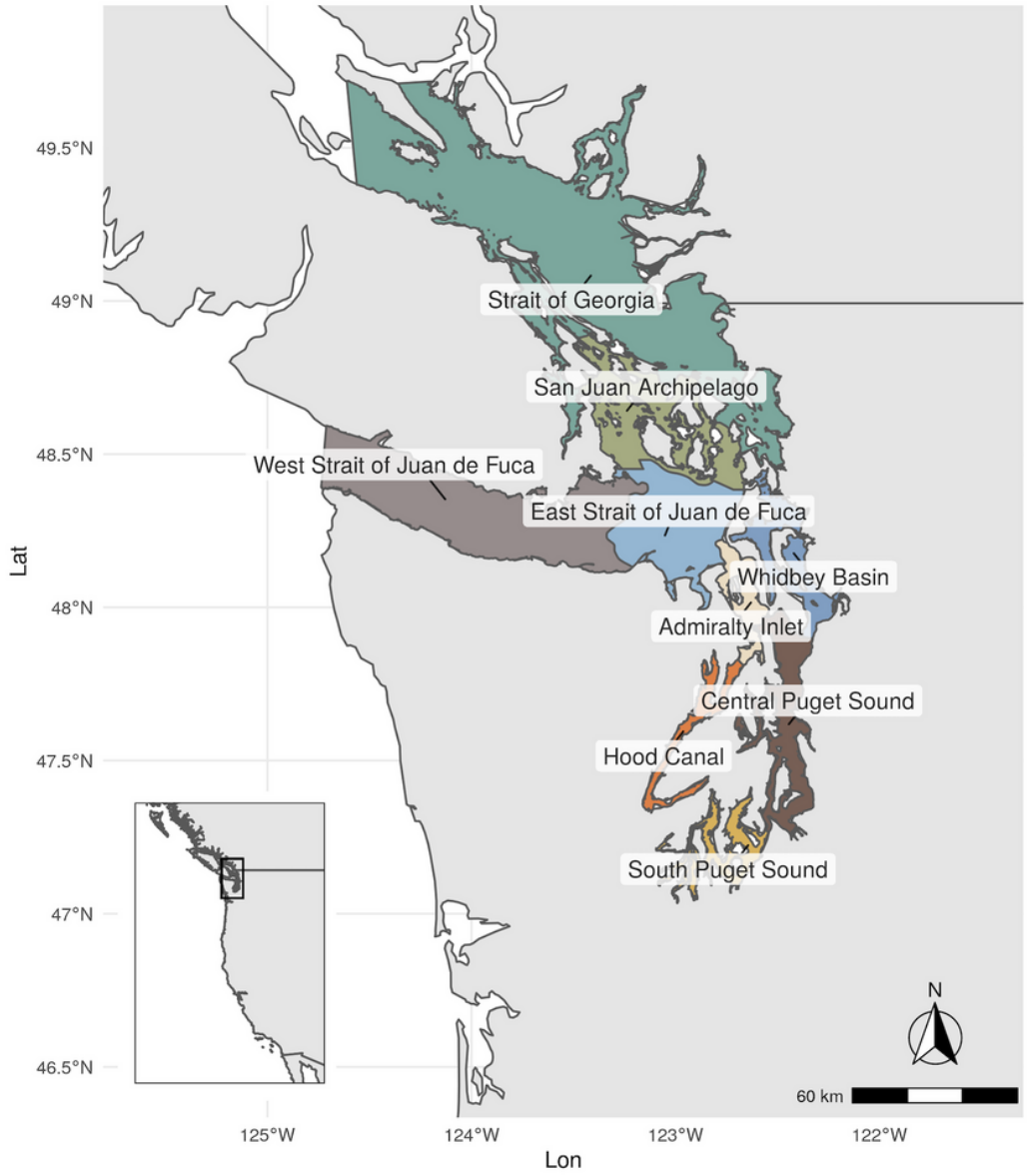

Figure 1

Map of Puget Sound. Labels correspond to basins.

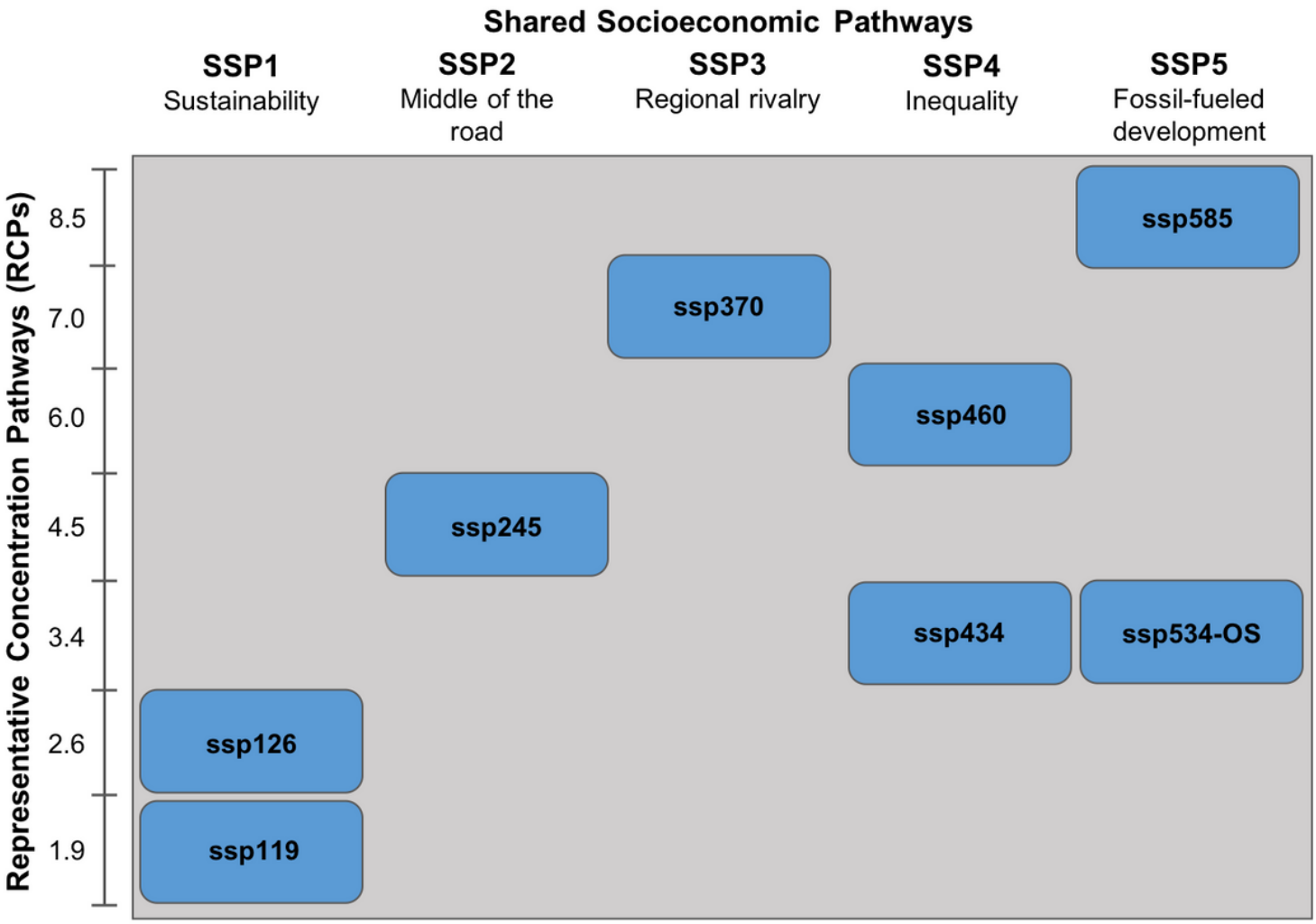

Figure 2

The eight CMIP6 scenarios (blue boxes) under ScenarioMIP. Each scenario is a combination of a Shared Socioeconomic Pathway (SSP), a projected outcome for society in the 21st century, with a Representative Concentration Pathway (RCP), the expected radiative forcing (W/m2) in 2100. Emissions scenarios logically can only stem from certain Shared Socioeconomic Pathways (SSPs), for instance, the sustainability-oriented SSP is not logically compatible with high emissions and higher RCPs. Modified from O'Neill et al. (2016).

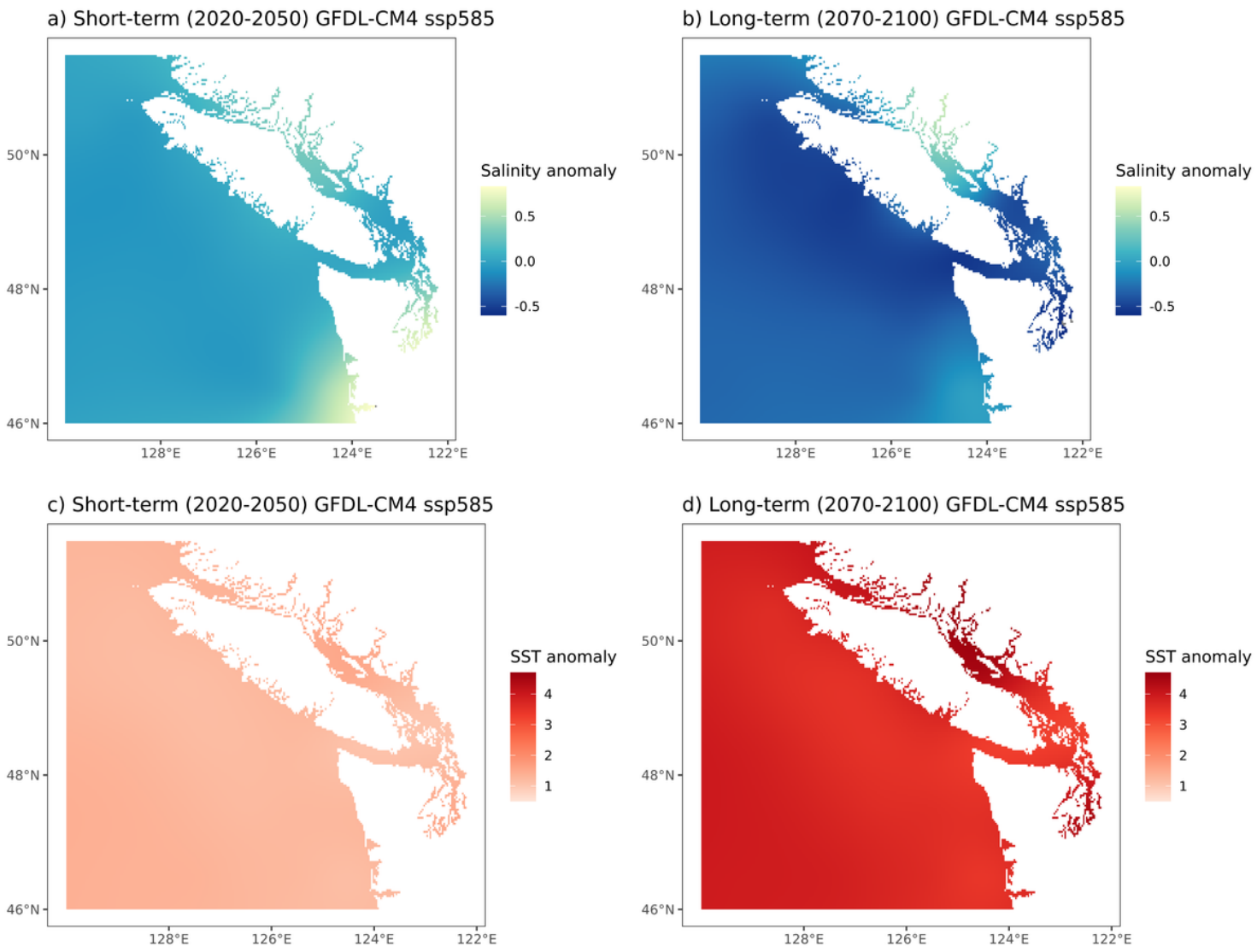

Figure 3

Interpolated anomalies for the GFDL-CM4 model scenario ssp585. The figure shows both short-term and long-term projections. Results were downscaled to a resolution of 3km. See Fig. S3 and Fig. S4 for interpolated anomaly projections for other scenarios and the CNRM-CM6-1-HR model. Salinity anomalies are reported in salinity units, and SST anomalies are reported in units of °C.

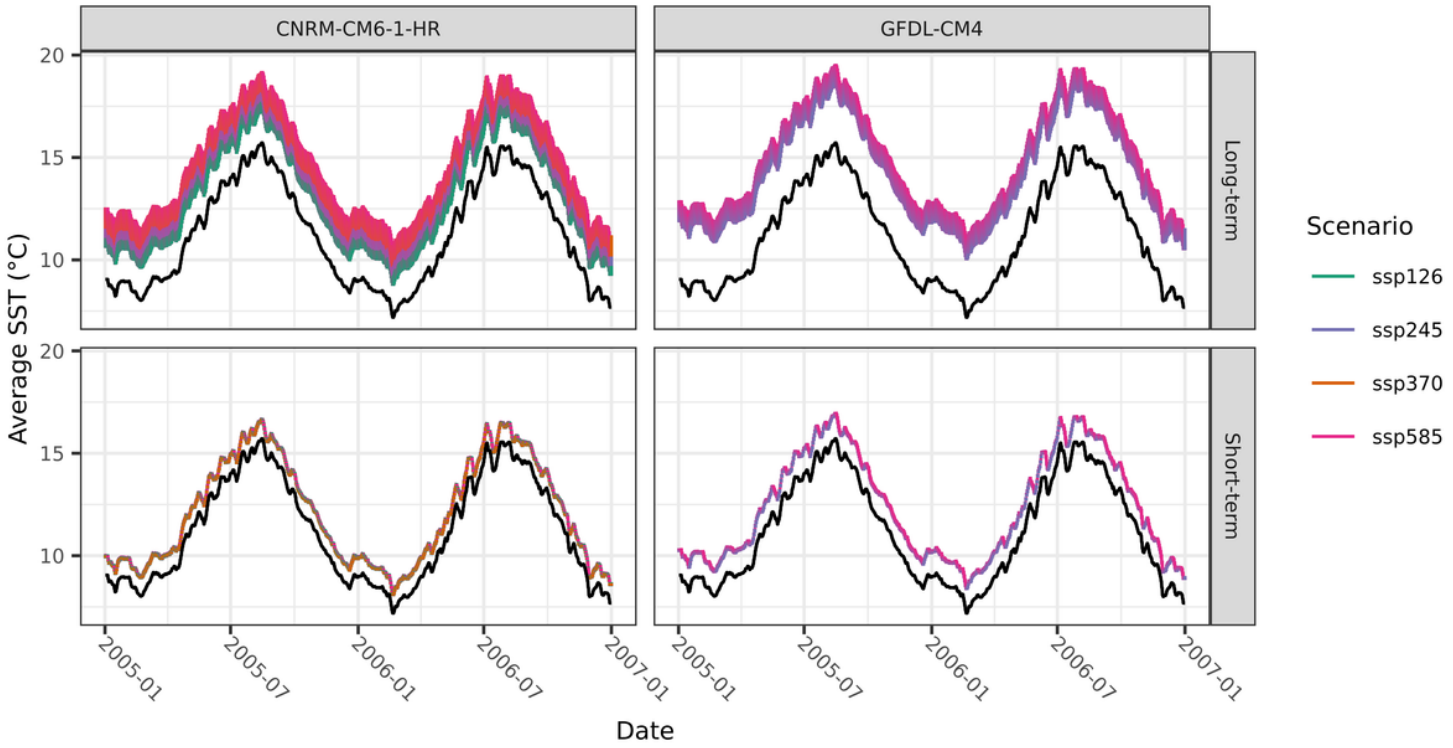

Figure 4

Average SST change for each scenario as forced by the ROMS time series for both models and long-term and short-term projections. The black line shows the temporal patterns that come from the ROMS baseline, which ran over a two-year period from 2005-2006. Scenarios are color coded, and range from low (ssp126) to high (ssp585) emissions. ssp126 and ssp370 are not included in the GFDL-CM4 model because it only ran two scenarios, ssp245 and ssp585.

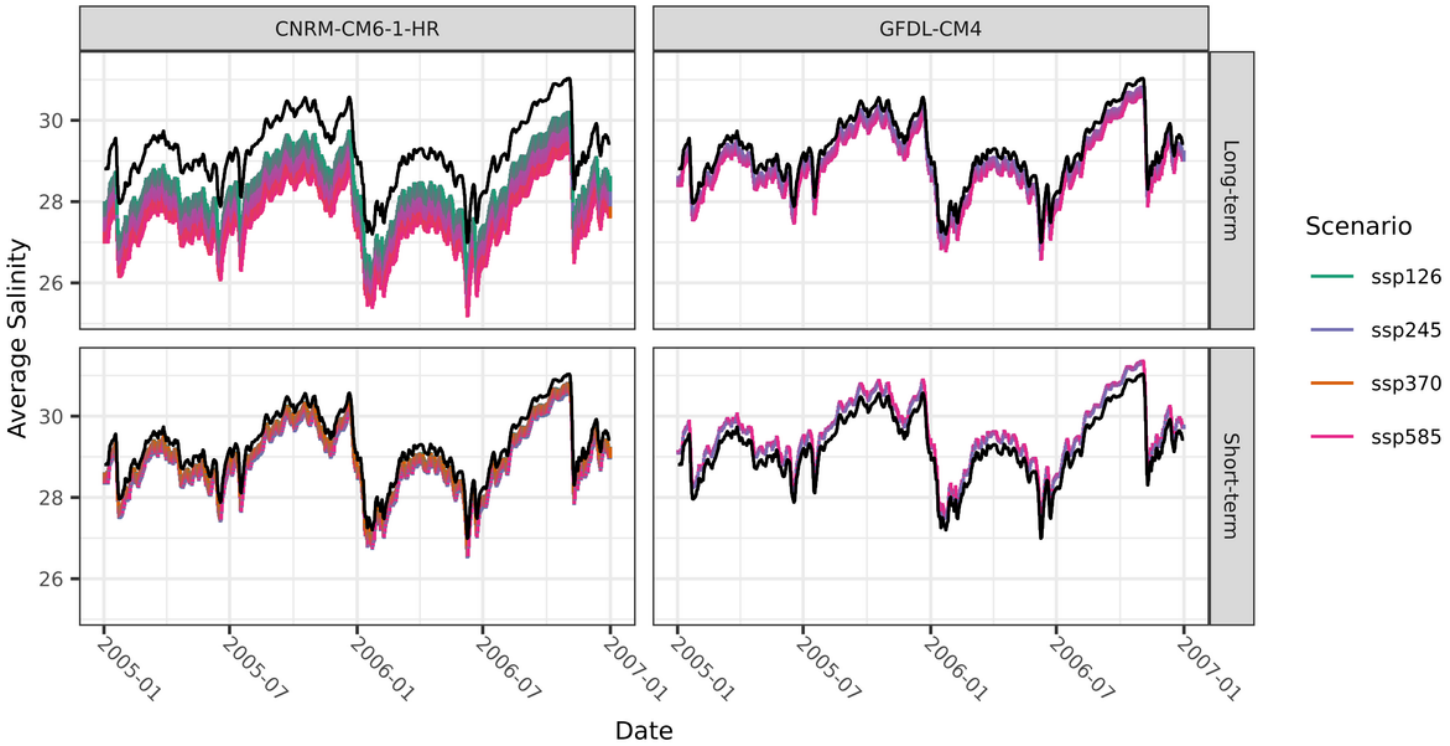

Figure 5

Average sea surface salinity change for each scenario as forced by the ROMS time series for both models and long-term and short-term projections. The black line shows the temporal patterns that come from the ROMS baseline, which ran over a two-year period from 2005-2006. Scenarios are color coded, and range from low (ssp126) to high (ssp585) emissions. ssp126 and ssp370 are not included in the GFDL-CM4 model because it only ran two scenarios, ssp245 and ssp585.

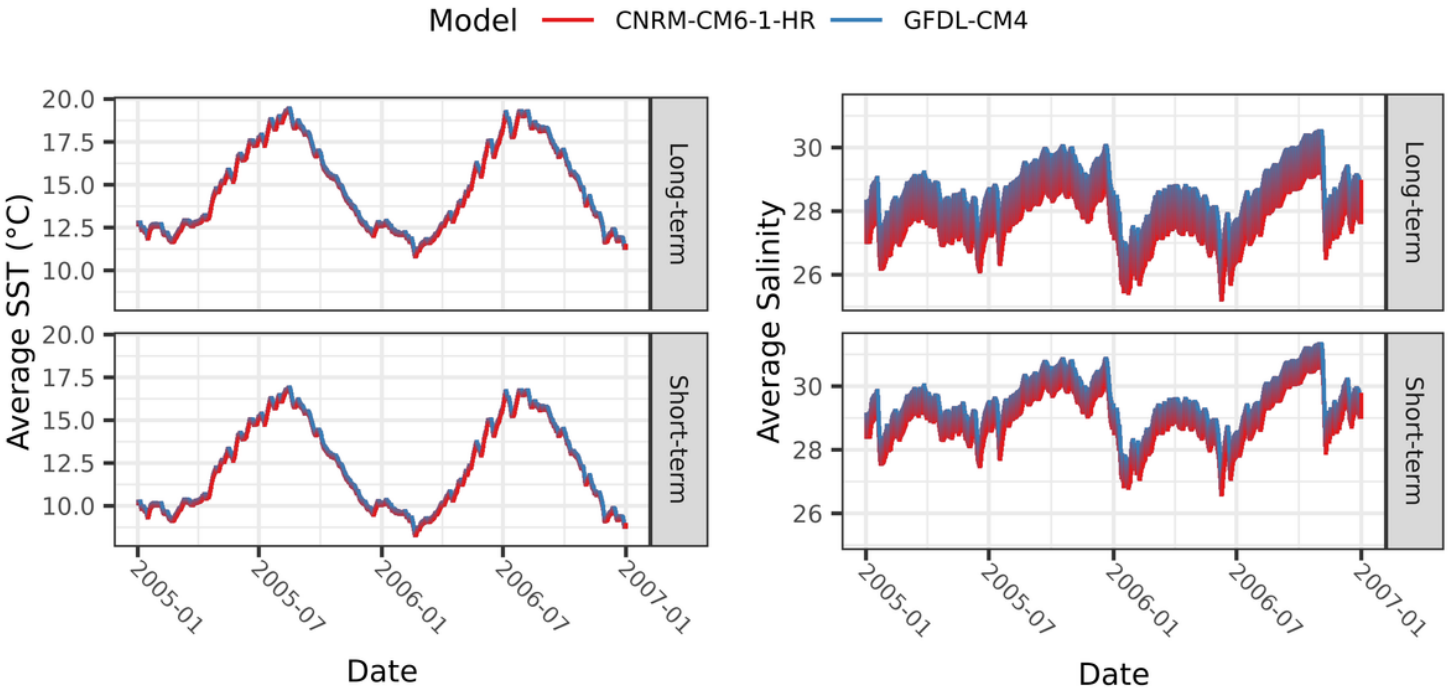

Figure 6

Variability between models for average SST and salinity change for ssp585 short-term and long-term projections. Temporal patterns come from the ROMS time-series, which ran from 2005-2006. See Fig. S5 for the ssp245 model variability.

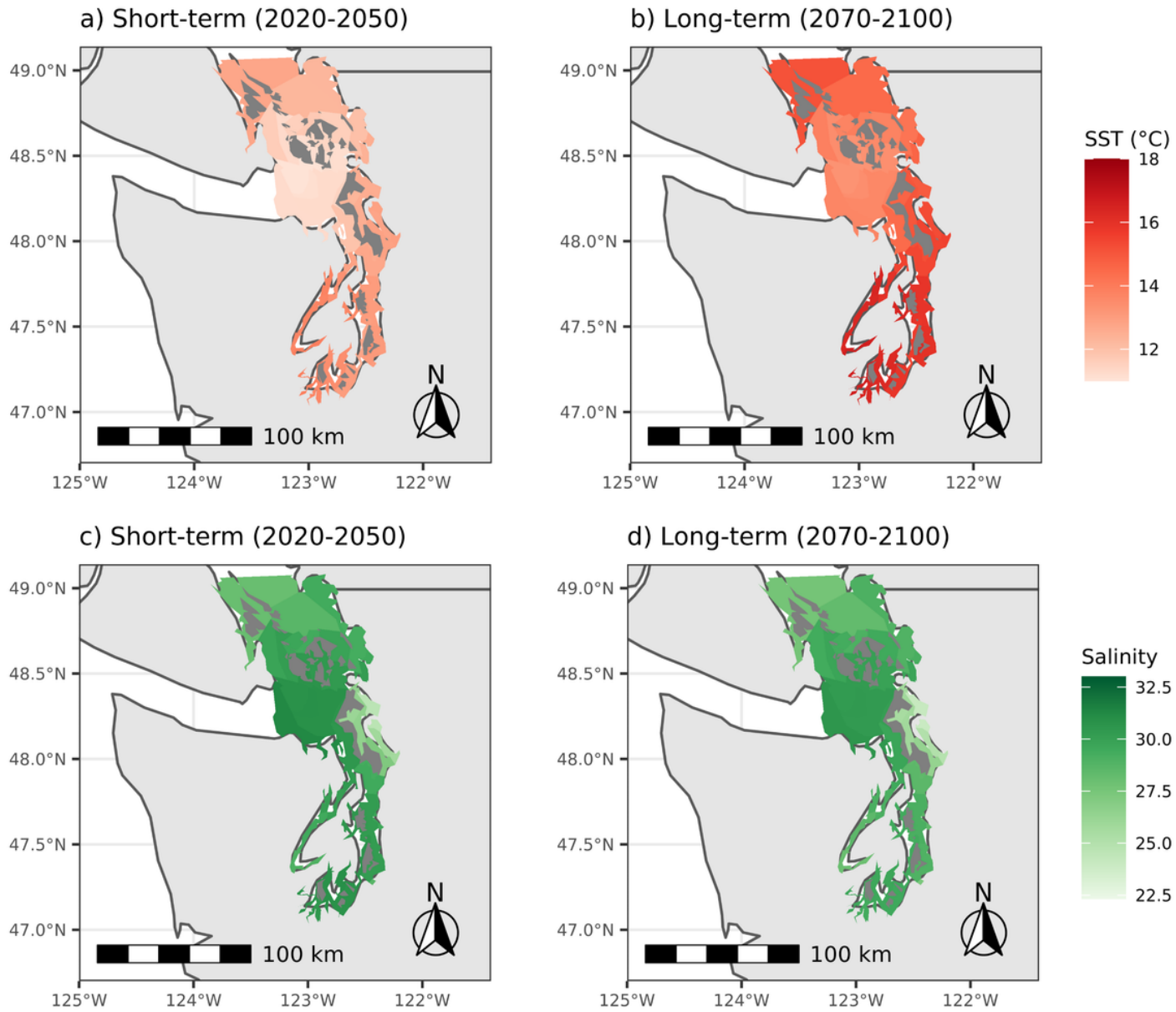

Figure 7

Spatial variations in downscaled projected SST and salinity for GFDL-CM4 ssp585 high-emissions scenario in both the short-term and long-term. Choropleth map polygons come from the Puget Sound Atlantis ecosystem model polygons (Morzaria-Luna et al. 2020a). The value within each polygon is the calculated average over the course of the two-year ROMS time-series. See Supplemental Material for more choropleth maps.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- Walkeretalsuppementarymaterial.pdf