

1 Comparative analysis of the performance of the GOFS,
2 PSY4 and AMSEAS ocean model frameworks in the
3 Virgin Islands and Puerto Rico coastal ocean

4 Sonaljit Mukherjee ^{*1}, Sennai Habtes ^{†1}, and Paul Jobsis ^{‡1}

5 ¹Center for Marine and Environmental Studies, University of the Virgin Islands

6 **Abstract**

7 This work compares the performance of 3 ocean model frameworks that currently produce
8 outputs of the ocean properties specific to the US Caribbean ocean; the Global Ocean Forecast
9 System (GOFS), US Navy Coastal Ocean Model for the American Seas (AMSEAS), and the
10 Daily Global Physical Bulletin (PSY4). Separate comparisons are done for the ocean properties
11 in the open ocean and the nearshore regions. For the open ocean, the model outputs are compared
12 with the AVISO satellite altimetry data for the sea-surface height anomaly (SSHA), the OSCAR
13 data for surface current velocities, and the G1SST satellite data for sea-surface temperature (SST).
14 For the nearshore analysis, the model outputs are compared with in-situ buoy measurements and
15 HOBO logger data in the nearshore regions. Our analysis shows that the PSY4 produces the
16 most realistic outputs of SSHA and surface current velocities in the open ocean, whereas all the
17 models produce a strong correlation in terms of the seasonal variability of the surface temperature
18 when compared to the G1SST data. The AMSEAS model, despite being a fine resolution regional
19 model, under-performs in terms of the surface current velocity outputs in the open ocean due to the
20 influence of the simulated submesoscale turbulence on the mesoscale variability. In the nearshore
21 regions, none of the models produce agreeable outputs on the SSHA and current velocities. These
22 findings provide useful insight on the applicability of the model outputs for various operations
23 that require oceanographic data specific to the US Caribbean ocean.

24 **1 Introduction**

25 The coastal ocean surrounding the US Virgin Islands (VI) and Puerto Rico (PR) boasts vibrant ma-
26 rine ecosystems. Many of the drivers regulating the ecological processes in the coastal ecosystems of
27 the region are strongly influenced by the physical and thermodynamic variables of the surrounding
28 coastal waters. For example, larval transport in the coastal ocean is influenced by large-scale pro-
29 cesses like $O(100 \text{ km})$ mesoscale eddies, as well as small-scale processes like surface gravity waves,
30 buoyancy-driven flows, atmospheric fluxes and both surface and internal tides [Pineda et al., 2007].
31 Furthermore, the resilience of coral reef ecosystems can be impacted by a variety of factors like the
32 seasonal variability of benthic temperature, the sedimentation rate and mechanical stress produced
33 by surface waves [Pineda et al., 2007]. A necessary step towards understanding the factors that fa-
34 cilitate or hamper the health and resilience of coastal ecosystems, is to have realistic estimates of

^{*}sonaljit.mukherjee@uvi.edu

[†]shabtes@gmail.com

[‡]pjobsis@uvi.edu

35 the circulation and thermodynamic characteristics of the surrounding ocean. Due to the complexity
36 of the instrumentation involved in obtaining 3-dimensional (3D) gridded data on the physical and
37 thermodynamic properties of the ocean, characterizing the ocean state and circulation is done using
38 computational ocean models coupled with data assimilation algorithms.

39 A numerical ocean circulation model with finite difference algorithm uses numerically discretized
40 prognostic equations that advance the momentum and scalar variables with respect to time. The grid
41 resolution of a numerical ocean model limits the dimension of the smallest circulation features that
42 a model can resolve. For example, a horizontal resolution of 1 km permits the model to represent
43 eddies with a minimum diameter of roughly 10 km. The inability to resolve turbulent fluxes at scales
44 lower than the permitted scale based on the grid resolution, creates a bias in the simulated ocean prop-
45 erties. This bias accumulates over time, producing unrealistic outputs of the momentum and scalar
46 fields. This problem is partially mitigated by constraining and adjusting the model outputs towards
47 the observed ocean properties using data assimilation [Marchesiello et al., 2001, Hoteit et al., 2018].
48 Such a combined framework of ocean models and data assimilation algorithms had been successfully
49 used to hindcast ocean circulation and scalar variability at various coastal and open ocean regions
50 [Chassignet et al., 2007, Rowley and Mask, 2014]. Notable forecast systems in operation include the
51 Global Ocean Forecast System (GOFS), the Relocatable nowcast/forecast system (RELO), the Global
52 Ocean Physical Analysis at $1/12^0$ (PSY4) by Mercator Ocean, Bluelink by the Commonwealth Sci-
53 entific and Industrial Research Organization (CSIRO) for Australia, Forecasting Ocean Assimilation
54 Model (FOAM) for the UK, and the Topaz Monitoring system for Norway [Hernandez et al., 2009,
55 Madec, 2008, Rowley and Mask, 2014, Oke et al., 2008, Storkey et al., 2010]. Each modeling frame-
56 work implements a unique set of parameters including but not limited to the vertical grid structure,
57 advection and diffusion algorithms, grid resolution and subgrid mixing parameterizations. Depend-
58 ing on the region of interest, these models use locally available observed data for assimilation and the
59 surface flux outputs from atmospheric models to produce 3D gridded outputs of the ocean state and
60 circulation.

61 As part of an international research initiative by the Global Ocean Data Assimilation Experiment
62 (GODAE), a comparative analysis between the different ocean forecasting systems have revealed the
63 strengths and weaknesses of the different modeling frameworks. These strengths and weaknesses
64 vary based on the model parameters, data used for assimilation, and the region of interest. These
65 comparative studies, conducted in the Tasman and Coral seas and along the east coast of Australia,
66 indicate that the Bluelink (CSIRO) provides the most realistic sea-surface height (SSH) variability,
67 whereas FOAM (UK) provides the most realistic subsurface temperature and salinity specific to the
68 Tasman and Coral Sea region [Oke et al., 2012].

69 For our region of interest, which is the US Caribbean ocean surrounding Puerto Rico (PR) and the
70 Virgin Islands (VI), there is currently no operational regional ocean modeling framework available
71 to aid to our ongoing marine research. Our long-term goal is to develop a coastal regional ocean
72 forecasting system for the US Caribbean ocean capable of resolving the flow around the relatively
73 small islands in the region with a sufficiently fine resolution that permits $O(1 \text{ km})$ submesoscale
74 eddies over a domain large enough to permit the modeling of $O(100 \text{ km})$ mesoscale eddies. As an
75 example, the blue rectangle in figure 1 depicts a typical domain for the proposed regional ocean model
76 for the US Caribbean ocean containing PR and the VI. Such a regional model will require 3D gridded
77 open-ocean data on the temperature, salinity and current velocities as boundary conditions. Since
78 the 3D gridded observational data in the open ocean is impossible to obtain due to complexities of
79 the instrumentation involved, we have to rely on the available coarse resolution model frameworks
80 that produce simulated 3D outputs of the ocean properties in the open-ocean surrounding the islands.
81 Therefore, it is necessary to compare the gridded outputs from existing model frameworks with the
82 available observational datasets for PR and the VI and to determine the strengths and weaknesses of
83 each model framework.

84 In this work, we do a comparative analysis of the performance of 3 ocean model frameworks

85 that provide 3D gridded data for the coastal ocean surrounding the VI and PR; the Global Ocean
86 Forecasting System (GOFS), the Navy Coastal Ocean Model for American Seas (AMSEAS), and
87 the Global Ocean Physical Analysis at $1/12^0$ (PSY4) by Mercator Ocean [Hernandez et al., 2009,
88 Madec, 2008, Rowley and Mask, 2014]. While the PSY4 and GOFS are global ocean forecasting
89 systems at a resolution of 10 km, the AMSEAS is a regional ocean forecasting system that operates
90 3 separate grids for the Alaskan seas, the US East, and the American Seas (AMSEAS) covering the
91 Gulf of Mexico and the Caribbean Sea at a resolution of 3 km. For assimilating observed data, both
92 the GOFS and the AMSEAS regional system use the NCODA [Cummings and Smedstad, 2013],
93 whereas the PSY4 uses the SEEK filter [Brasseur and Verron, 2006].

94 We evaluate the performance of these model frameworks by comparing their outputs with available
95 observational data on the sea-surface height anomaly (SSHA), surface current velocities, seasonal
96 variability of the sea-surface temperature (SST) and the in-situ benthic temperature. Section 2 provides
97 a brief overview of the circulation in the Caribbean Sea with a particular focus on the coastal
98 circulation of the US Caribbean. Section 3 provides a brief overview of the currently available model
99 frameworks for the islands in the region, namely the PSY4, GOFS and the AMSEAS. Section 4 provides
100 an overview of the available observational data and the nearshore ocean properties for the US
101 Caribbean. In section 5, we explain the different metrics and analyses used to evaluate the model
102 performance by comparing simulated outputs with the observed data mentioned above. Section 6 discusses
103 the results from the analysis of model performance and section 7 summarizes our conclusions
104 regarding which circulation model frameworks are appropriate for use in the US Caribbean ocean.

105 **2 Ocean Circulation Surrounding Puerto Rico and the Virgin Islands**

106 Puerto Rico and the Virgin Islands lie along the northern arc of the Antilles islands, a group of islands
107 bordering the northeastern rim of the Caribbean Sea (figure 1). The ocean circulation surrounding
108 these islands is largely influenced by the westward inflow of the Atlantic gyre circulation into the
109 Caribbean Sea through the passages between the islands of the lesser Antilles. The Caribbean Current,
110 spanning the southern portion of the Caribbean Sea between latitudes 13^0 and 16^0 N, is largely driven
111 by the inflow of the Atlantic Meridional Overturning Circulation (AMOC) through the Windward and
112 Leeward island passages [Johns et al., 2002]. This inflow of the AMOC forms approximately two-
113 thirds of the net inflow from the Atlantic Ocean into the Caribbean Sea. The remaining one-third of
114 the inflow occurs between the passages of the islands in the Greater Antilles; the Anegada-Jungfern
115 passage complex to the east separating the Virgin Islands from the Lesser Antilles beginning with
116 Anguilla and St. Maarten, and the Mona passage to the west between Puerto Rico and Hispaniola
117 [Johns et al., 2002]. The Anegada passage facilitates the flow of mid-depth Atlantic water into the
118 Virgin Islands basin, and the Jungfern passage allows the flow of the Atlantic water into the Caribbean
119 Sea [Fratantoni et al., 1997]. The strength of the Caribbean current is geostrophically enhanced by
120 the intensification of the north-south density gradient due to the freshwater flux from the Orinoco and
121 Amazon rivers [Chérubin and Richardson, 2007]. This freshwater plume can move northwestward
122 through the Caribbean Sea at times reaching the southern coastline of St. Croix of the VI, creating
123 turbulent wakes in the offshore region of the northeastern coast of St Croix [Chérubin and Garavelli,
124 2016]. The flow along the northern coastline of the Greater Antilles islands has been characterized
125 as a discontinuous eddy field that transports warm water northwestward as it merges with the Florida
126 current [Gunn and Watts, 1982]. Simulating the complexity of these features is beyond the capability
127 of the currently operational global ocean models due to coarse resolutions. Therefore, it is necessary
128 to develop a downscaled ocean circulation model with a resolution less than 1 km to realistically
129 simulate the small-scale features and their impact on the mesoscale circulation.

131 3 Ocean Model Frameworks

132 Currently, the model frameworks that provide simulated outputs of the coastal ocean circulation
133 around PR and the VI are the GOFS [Hernandez et al., 2009], the AMSEAS [Rowley and Mask,
134 2014] and the PSY4 [Madec, 2008]. Details on the parameters of these model frameworks are pro-
135 vided in table 1.

136 3.1 GOFS

137 The Global Ocean Forecast System (GOFS¹), created as part of the Global Ocean Data Assimila-
138 tion Experiment (GODAE) [Hernandez et al., 2009], uses the Hybrid Coordinate Ocean Model (HY-
139 COM) [Chassignet et al., 2007]. The HYCOM is a primitive equation general circulation model
140 using a vertical coordinate system that shifts from isopycnal coordinates in the stratified open ocean
141 to terrain-following coordinates in the shallow coastal regions and z-level coordinates in the upper
142 ocean boundary layer [Chassignet et al., 2007]. The horizontal discretization in GOFS is based on an
143 orthogonal curvilinear coordinate system with a horizontal grid resolution of $1/12^0$. The surface forc-
144 ing used by GOFS is obtained from the Navy Global Environmental Model (NAVGEM) [Whitcomb,
145 2012]. There is no tidal forcing implemented in the GOFS model framework. Detailed specifics on
146 the GOFS system are provided in table 1.

147 The absence of realistic turbulent fluxes that occur at scales smaller than the grid resolution of
148 an ocean model, results in a bias in the simulated ocean properties from the model outputs. To mit-
149 iigate this bias, observed data are assimilated into the model outputs using various data assimilation
150 techniques. The GOFS uses the Navy Coupled Ocean Data Assimilation (NCODA), a 3D multi-
151 variate optimum interpolation scheme [Cummings and Smedstad, 2013] that assimilates all quality-
152 controlled observational data including satellite SST, altimetry derived SSH, microwave-derived sea
153 ice concentration, in-situ temperature and salinity measurements from ships, drifters, buoys, profiling
154 floats, XBTs (Expendable Bathythermographs), CTDs (Conductivity, Temperature and Depth Sen-
155 sors) and gliders. The NCODA version 3.1 generates subsurface temperature and salinity fields from
156 the SST and SSH using an Improved Ocean Synthetic Profile (ISOP) technique [Helber et al., 2013],
157 and assimilates the subsurface fields into the model outputs using 3D Variational Data Assimilation
158 (3DVAR, Barker et al. [2004]). The NCODA is tuned to process the observed data and constrain the
159 model outputs towards the observed data on the order of spatial scales equivalent to or larger than the
160 O(100 km) mesoscale [Carrier et al., 2019].

161 The GOFS provides 3-hourly instantaneous outputs on the momentum and scalar properties of
162 the global oceans. In our analysis, we use the previously simulated hindcast outputs from the GOFS
163 model in the Northern Caribbean sea, averaged over 1 day. The outputs can be obtained from the
164 HYCOM server.

165 3.2 PSY4

166 The Daily Global Physical Bulletin at $1/12^0$ (PSY4²), maintained by the non-profit company Mercator
167 Ocean, uses version 3.1 of the NEMO (Nucleus for European Modeling of the Ocean) [Madec, 2008].
168 The NEMO uses a tripolar ORCA grid [Madec and Imbard, 1996] with a horizontal resolution of
169 $1/12^0$. The vertical coordinate is discretized into 50 levels with resolution increasing from 1 m near
170 the surface to 450 m at the bottom. The PSY4 uses atmospheric forcing provided by the European
171 Center for Medium Range Weather Forecasts (ECMWF) with a sampling time of 3 hours, and does
172 not use any tidal forcing. For the data assimilation, the PSY4 uses the SEEK filter, which is a reduced-

¹<https://tds.hycom.org/thredds/catalog.html>

²<https://marine.copernicus.eu/>

173 order Kalman filter with a 3D multivariate modal decomposition of the background error and a 7-day
174 assimilation cycle [Brasseur and Verron, 2006].

175 The PSY4 provides hourly hindcast data on the momentum and scalar properties of the global
176 oceans. We use the daily averaged hindcast outputs from the PSY4 in the Northern Caribbean Sea,
177 which can be accessed from the Copernicus Marine Service server.

178 **3.3 AMSEAS**

179 The Relocatable ocean nowcast/forecast system [Rowley and Mask, 2014], operated by the Naval
180 Oceanographic Office (NAVOCEANO), uses the Navy Coastal Ocean Model (NCOM³) at a hori-
181 zontal resolution of $1/36^0$, along with the NCODA system for data assimilation. The NCOM is a
182 primitive equation baroclinic, hydrostatic, Boussinesq ocean model with a free surface [Barron et al.,
183 2006]. It uses an orthogonal curvilinear grid for horizontal discretization. The vertical grid used
184 by RELO consists of a number of terrain following σ coordinate levels from the surface, and Carte-
185 sian z-levels below (table 1). The NCOM is used for regional simulation within the Alaskan domain
186 covering the Gulf of Alaska and the Northeast Pacific, the US east coast (USEAST) and the Amer-
187 ican seas (AMSEAS) spanning the Gulf of Mexico and the Caribbean Sea (figure 2). The NCOM
188 AMSEAS uses the 15 km application of the Navy Coupled Ocean/Atmosphere Mesoscale Prediction
189 System (COAMPS) for surface forcing [Hodur, 1997], and the GOFS model outputs at $1/12^0$ resolu-
190 tion [Chassignet et al., 2007, 2009] for boundary conditions. Tidal forcing in the NCOM AMSEAS
191 regional setup is provided by the OTIS tidal package [Egbert and Erofeeva, 2002].

192 While the GOFS and PSY4 are global ocean forecast models, the NCOM AMSEAS is a regional
193 model setup that uses the GOFS model outputs as boundary conditions and the NCODA for assimilat-
194 ing the observed data. The AMSEAS provides 3-hourly instantaneous outputs on the momentum and
195 scalar properties in the Caribbean sea. In our analysis, we use the previously simulated oceanographic
196 outputs by the AMSEAS model in the US Caribbean ocean, averaged over 1 day. The AMSEAS out-
197 puts are available on the NOAA NCOM server.

198 **4 Observed Data**

199 Gridded observed data available for the physical and thermodynamic properties of the Caribbean Sea
200 are the sea-surface height anomaly (SSHA) produced by Archiving, Validation and Interpretation of
201 Satellite Oceanographic data (AVISO, AVISO-Altimetry [1996], [Guerrero et al., 2004]), sea-surface
202 temperature (SST) from the Group for High Resolution Sea Surface Temperature (G1SST, section
203 4.3), and surface current velocity estimates from the Ocean Surface Current Analysis Real-time (OS-
204 CAR, Bonjean and Lagerloef [2002], Johnson et al. [2007]).

205 **4.1 AVISO**

206 AVISO provides gridded satellite altimetry data products including SSHA and geostrophic velocities
207 at a spatial resolution of $1/4^0$ of latitude, and a temporal resolution of 1 day. The AVISO SSHA data
208 is prepared by merging the altimetry measurements from altimeters aboard the TOPEX/Poseidon, En-
209 visat, Jason-1 and OSTM/Jason-2, satellite platforms and estimated with respect to a 20-year average
210 [Blanc et al., 1996, Guerrero et al., 2004]. In the open ocean, away from the influence of shallow
211 coastal bathymetry, the SSHA variability is governed by wind-driven circulation, atmospheric pres-
212 sure and internal density gradients. Hence, the SSHA variability in the open ocean is an important
213 source of information for deducing the subsurface ocean characteristics. Detailed specifics of the
214 AVISO data are provided in table 2.

³<https://www.ncei.noaa.gov/products/weather-climate-models/fnmoc-regional-navy-coastal-ocean>

215 **4.2 OSCAR**

216 OSCAR is a NASA funded research project that provides surface current velocities averaged over
217 the top 30 m of the ocean and is available at 5-day intervals. The OSCAR surface current data is
218 developed by interpolation and analysis of SSHA, surface wind velocity and SST data obtained from
219 satellite and in-situ measurements. The governing equations used to compute these velocities are
220 based on a quasi-linear and quasi-steady approach with geostrophic balance, Ekman–Stommel shear
221 dynamics and a complimentary term from the surface buoyancy gradient [Bonjean and Lagerloef,
222 2002, Johnson et al., 2007]. The OSCAR data is available with a horizontal resolution of $1/3^0$ and
223 averaged over 5 days. The OSCAR provides reasonable estimates of the surface current velocities
224 in the tropical open ocean [Sikhakolli et al., 2013]. Detailed specifics on the OSCAR dataset are
225 provided in table 2.

226 **4.3 G1SST**

227 The Global 1 km Sea Surface Temperature Analysis (G1SST), maintained by the Group for High
228 Resolution Sea Surface Temperature (GHRSSST), uses satellite and in-situ data of ocean surface tem-
229 perature and produces daily averaged SST data over a grid with 1 km resolution using a 2-dimensional
230 variational data assimilation (2DVAR) algorithm [Chao et al., 2009]. The G1SST uses SST data from
231 the Geostationary Operational Environmental Satellite (GOES), Advanced Very-High Resolution Ra-
232 diometer (AVHRR), Moderate Resolution Imaging Spectroradiometer (MODIS), Spinning Enhanced
233 Visible and Infrared Imager (SEVIRI), Advanced Microwave Scanning Radiometer-EOS (AMSR-E),
234 Multi-Functional Transport Satellite 1R (MTSAT-1R) radiometer, and in-situ data from moored buoys
235 and drifters in its analysis. The G1SST data is available for the Caribbean Sea and nearshore areas in
236 gridded format with a sampling time of one day. Detailed specifics on the G1SST dataset are provided
237 in table 2.

238 **4.4 Nearshore In-Situ Measurements**

239 While the open ocean circulation is governed by wind forcing and quasi-geostrophic (QG) instabili-
240 ties, the nearshore circulation is mostly characterized by wind forcing, boundary-layer effects, surface
241 gravity waves, and the impact of shallow coastal bathymetry on open ocean mesoscale flow [Vic et al.,
242 2015, Pineda et al., 2007]. For a numerical model to realistically simulate these nearshore small-scale
243 processes, the resolution of the model has to be sufficiently fine. Due to a finer resolution of 3 km
244 in the AMSEAS model, the AMSEAS permits a more realistic representation of the complex coastal
245 bathymetry compared to the GOFS and PSY4. Moreover, the fine resolution of the AMSEAS also
246 enables it to partially resolve the $O(10$ km) submesoscale turbulence. Therefore, it is important to
247 explore whether there is any improvement of model performance due to the fine resolution of the
248 AMSEAS, compared to the coarse resolution of the GOFS and PSY4 in the nearshore regions.

249 The resolution of the OSCAR and AVISO datasets are too coarse to capture the nearshore vari-
250 ability associated with shallow bathymetry. Moreover, the OSCAR dataset does not take the coastal
251 bathymetry into account in the computation of the current velocities. Therefore, a comparison of
252 the model performance for the nearshore surface current velocity will require in-situ data measured
253 in the nearshore areas of the VI and PR. This available in-situ data includes moored-buoy measure-
254 ments of surface currents and surface temperature by the Caribbean Coastal Ocean Observing System
255 (CariCOOS), and benthic temperature measurements by HOBO temperature data loggers at various
256 coral reef sites near the coastline as part of the Territorial Coral Reef Monitoring Program (TCRMP)
257 [Smith et al., 2015]. The Caribbean Coastal Ocean Observing System (CariCOOS) maintains a num-
258 ber of moored buoys in coastal regions throughout the US Caribbean [Morell et al., 2015]. The buoys
259 provide hourly data on the surface current velocities measured by Acoustic Doppler Current Profil-
260 ers (ADCPs) and surface temperature measured by CTDs. In our analysis, we use the data from 4

261 different buoys; the Ponce buoy (17.86^0 N, -66.52^0 W), San Juan buoy (18.47^0 N, -66.1^0 W), St
262 John buoy (18.25^0 N, -64.76^0 W) and the Vieques buoy (18.26^0 N, -65.46^0 W) (figure 3). The
263 temperature at each of these locations were measured at a depth of 1 m below the water line. The
264 ADCP current data at these locations were measured at multiple bins placed 1 m apart along a vertical
265 profile at each location. The shallowest bin is at 2 m from the surface, whereas the deepest bin is at
266 the benthic depth of the location which is 19 m at Ponce, 32 m at San Juan, 44 m at St John, and 30
267 m at Vieques. The current data that we used in our analysis is a depth average of all the data collected
268 at the bins for each location up to a depth of 30 m from the surface. We chose a depth of 30 m for
269 the depth averaging because the mixed layer in the US Caribbean region varies from 20 m in summer
270 to 60 m in the winter. The model outputs of the current velocities were obtained as a vertical average
271 within the surface mixed layer.

272 As part of the Territorial Coral Reef Monitoring Program (TCRMP), a program to monitor the
273 status of coral reefs in the US Virgin Islands, HOBO data loggers were used to measure benthic
274 temperature hourly at coral reef sites across the islands [Smith et al., 2015]. In this study, we compare
275 the seasonal temperature variability of TCRMP sites at Jacks Bay, St. Croix, and two offshore Cays
276 in St. Thomas, Savana (18.34^0 N, -65.08^0 W) and St. James (18.29^0 N, -64.83^0 W; figure 3) with
277 the benthic temperature variability from the model outputs at the same locations. The HOBO loggers
278 were placed at the benthic depths of 27 m at Jacks Bay, 16 m at Savana, and 13 m at St James.

279 **5 Validation Techniques**

280 We evaluate and compare the performance of the models with respect to the remotely estimated open-
281 ocean data and the nearshore in-situ data in the US Caribbean in terms of the simulated SSH, current
282 velocities and the temperature. Due to sparse availability of data on the interior temperature and
283 velocity fields in the Caribbean Sea, a comparison of the model derived interior fields with observed
284 data is not possible. Therefore, we use the available gridded SSH and surface current velocity
285 datasets from AVISO and OSCAR respectively, and in-situ temperature data from CariCOOS and
286 TCRMP to evaluate the accuracy of the individual model frameworks for the US Caribbean ocean.
287 Our analysis is based on assessing the model performance in terms of the oceanographic properties in
288 the open ocean and nearshore regions that will be useful for operational oceanography stakeholders
289 in the US Caribbean islands (i.e. scientists, managers, fishermen and captains), and have the requisite
290 observed or in-situ data for comparative analysis. As such, we have identified the open-ocean SSH,
291 mesoscale eddies, both open-ocean (100 km away from the coastlines, depth \sim 4 km) and nearshore
292 (less than 1 km from the coastlines, depth \sim 0.5 km) surface currents, and the surface and benthic
293 ocean temperature for our analysis.

294 The coastal ocean circulation surrounding the islands is heavily influenced by the interaction of
295 shallow coastal bathymetry with the mesoscale eddy variability in the open ocean. Mesoscale eddies
296 can be identified in the AVISO SSH as large meanders of $O(100$ km) diameter with a spatial gradient
297 in the SSH along their periphery. The resolution of the AMSEAS, GOFS and PSY4 models are
298 adequate to resolve the mesoscale eddies in the Caribbean Sea. Hence, we compare the spatial extent
299 of the $O(100$ km) mesoscale features in these model outputs with the observed features in the AVISO
300 data using the following methods.

301 **5.1 SSH Analysis**

302 We compare the spatial and temporal variability of SSH from the AVISO and the model outputs in
303 2016 using plan view plots and Hovmöller diagrams respectively. A plan view plot shows the spatial
304 variability of an ocean property at a fixed time, whereas the Hovmöller diagram shows the temporal
305 variability of the property along a fixed transect. Using the plan view plots, we examine the mesoscale
306 variability at 4 randomly chosen dates in March, June, October and December 2016 (figure 6). At

307 each of these dates, we identify the O(100 km) mesoscale features in the AVISO SSH and find out
 308 whether the model outputs show similar features at the same locations.

309 Using the Hovmöller diagrams, we plot the SSH from the AVISO data and model outputs along
 310 a meridional transect (figure 1) in the Anegada passage over a 1-year period in 2016 (figure 7). The
 311 Anegada passage is chosen because the flow through the Anegada passage largely governs the local
 312 circulation around PR and the VI [Fratantoni et al., 1997]. A comparison of the temporal variability of
 313 SSH in this region can provide valuable insight on the capability of regional ocean models to resolve
 314 the local flow around the islands. Using a Hovmöller diagram, we study the temporal variability in
 315 the meridional gradient of the AVISO SSH in the Anegada passage over a 1-year period in 2016.

316 The temporal variability of the SSH in the Anegada passage is further studied using the power
 317 spectral density (PSD) computed from the time series of the SSH, averaged over the zonal range
 318 from 16° to 20° (figure 8). We examine the PSD plot to compare the magnitude of the variance of
 319 SSH at different frequencies corresponding to the large and small temporal scales.

320 5.1.1 Okubo-Weiss parameter

321 We assess the mesoscale eddy variability from the modeled and observed SSH using the Okubo-
 322 Weiss parameter, a measure of the strength of the vorticity field relative to the strain field [Isern-
 323 Fontanet et al., 2003, Okubo, 1970]. The Okubo-Weiss parameter W is given as

$$324 W = S_n^2 + S_s^2 - \zeta^2 \quad (1)$$

325 where $S_n = \partial_x u - \partial_y v$ is the compressive strain, $S_s = \partial_x v + \partial_y u$ is the shear strain, and $\zeta = \partial_x v - \partial_y u$
 326 is the relative vorticity. The variables u and v are the barotropic velocities derived from the SSH. A
 327 mesoscale eddy is defined as a closed region of O(100 km) diameter where $W \leq -0.2\sigma$ where σ is
 328 the spatial standard deviation of the W field corresponding to the same sign of ζ [Isern-Fontanet et al.,
 329 2003]. Therefore, in order to separately identify the cyclonic and anti-cyclonic mesoscale eddies, we
 330 calculate the standard deviation σ separately for the regions corresponding to $\zeta > 0$ and $\zeta < 0$.
 331 The strain field is defined as a region where $W > 0.2\sigma$, implying that the strain field dominates the
 332 vorticity field by strength.

332 5.1.2 Taylor Diagram

333 The relative performance of a model output is best evaluated by the extent of the statistical deviation
 334 of each output from the observed data and the correlation of each output with the observed data.
 335 Taylor diagrams provide an effective means to visualize the statistical deviations and correlations
 336 of the model outputs. A Taylor diagram [Taylor, 2001] is a polar coordinate representation of the
 337 following statistical measurements: root mean square deviation ($RMSD$) of the model output from
 338 the observed data, cross-correlation (R) of the model output and the observed data, and the standard
 339 deviation (σ) of the model output. The $RMSD$ of the model output with respect to the observed data
 340 is calculated as

$$341 RMSD = \left\{ \frac{1}{N} \sum_{n=1}^N [(h_n - \bar{h}) - (o_n - \bar{o})]^2 \right\}^{1/2} \quad (2)$$

342 where h and o are the model output and the observed dataset respectively and N is the sample size.
 343 The overline represents the mean.

344 The standard deviation of the model output is calculated as

$$\sigma = \sqrt{\frac{1}{N} \sum_{n=1}^N (h_n - \bar{h})^2} \quad (3)$$

345 The cross-correlation of model output with the observed data is calculated as

$$346 R = \frac{1}{\sigma_h \sigma_o} \cdot \frac{1}{N} \sum_{n=1}^N (h_n - \bar{h})(o_n - \bar{o}) \quad (4)$$

345 where σ_h and σ_o are the standard deviations of the model output and the observed data respectively.
346 The $RMSD$, σ and R satisfy the following relationship:

$$RMSD^2 = \sigma_h^2 + \sigma_o^2 - 2\sigma_h\sigma_oR \quad (5)$$

347 In a Taylor diagram (figure 4), each model output and the observed data are represented by specific
348 markers. The observed data marker lies at the base line where the correlation is 1, and the radial
349 distance of each model output marker from the observed data marker denotes the $RMSD$. The
350 distance of each marker from the center of the radial axis denotes the standard deviation σ of the
351 model output or observed data. The arc length along the azimuthal axis (circumference) denotes the
352 cross-correlation coefficient between the model output and the observed data. The performance of the
353 model is interpreted from the relative distance of the model's marker to the marker for the observed
354 data. A larger radial distance from the origin implies a higher standard deviation, indicating that
355 the model output contains more small-scale variability and is noisier than the observed data [Oke
356 et al., 2012]. A shorter distance of the model output marker from the observed data marker implies
357 a lower $RMSD$ and a higher correlation with respect to the observed data. Both higher correlation
358 and lower $RMSD$ can be interpreted as better model performance. Henceforth, the assessment of the
359 model performance is based on how similar the model output is to the observed data, and therefore is
360 confined to the resolution of the available observed data.

361 We evaluate the model performance in terms of the SSHA, surface current velocities and sea-
362 surface temperature (SST) by comparing the statistical deviations and cross-correlations of the model
363 outputs with respect to the gridded satellite data. For the SSHA data, we conduct two separate analysis
364 using Taylor diagrams for the model outputs in the Caribbean Sea and along a meridional transect in
365 the Anegada passage (figure 1). Prior to the Taylor diagram analysis, the modeled SSHA outputs and
366 the AVISO dataset are prepared in the following manner: (i) at each sampling time, the model output
367 is re-mapped to the horizontal latitude-longitude grid of the AVISO dataset; (ii) for each model output
368 and the AVISO dataset, the 1-dimensional arrays along the time-axis at each of the grid points on the
369 re-mapped domain, are concatenated to form a single 1-dimensional flattened array; (iii) Standard
370 deviation, $RMSD$ and cross-correlation coefficients were calculated using the flattened 1-dimensional
371 arrays of the model outputs and the observed datasets.

372 5.1.3 Power Spectral Density (PSD)

373 The contribution of submesoscale and quasi-geostrophic mesoscale turbulence to the variance of the
374 momentum and scalar fields can be estimated using the power spectral density (PSD) of the data
375 as a function of the wavenumber. With enhanced spatial resolution in the satellite observations and
376 numerical models, the variance of different oceanographic properties like the sea-surface temperature
377 (SST), current velocity or the sea-surface height anomaly (SSHA) had been discovered to be mostly
378 governed by $O(10 \text{ km})$ submesoscale turbulence along with $O(100 \text{ km})$ mesoscale quasi-geostrophic
379 turbulence [Callies and Ferrari, 2013]. In numerical models with a coarse resolution of $O(10 \text{ km})$, the
380 velocity variance is mostly dominated by quasi-geostrophic mesoscale turbulence, which results in
381 the PSD being proportional of κ^{-3} where κ is the wavenumber. In contrast, submesoscale turbulence
382 results in the velocity and tracer variances to be proportional to κ^{-2} , which had been noted in fine-
383 resolution glider measurements and numerical ocean models [Callies and Ferrari, 2013, Brannigan
384 et al., 2015, Castro et al., 2017]. On a logarithmic plot of the PSD as a function of the wavenumber,
385 submesoscale turbulence results in a flatter spectral slope compared to mesoscale turbulence.

386 We compared the spatial variance of the current velocities, SSHA and SST from the model outputs
387 at different spatial scales using the PSD (figure 5). For each data, the PSD is calculated as a function
388 of the longitudinal wavenumber, followed by averaging over the entire range of latitudes and sampling
389 times available in the data.

390 **5.2 Surface Current Velocities**

391 Model performance of the simulated surface current velocities is assessed for both the open ocean
392 and nearshore coastal waters. Open ocean refers to the regions of the Caribbean Sea surrounding
393 the islands where the deep bottom bathymetry has negligible impact on the surface flow. Nearshore
394 refers to the regions near the coastline where the flow is governed by the interaction of shallow coastal
395 bathymetry and the open-ocean mesoscale flow. For the open ocean, we use Taylor diagrams to
396 compare the statistical deviations and correlations of the simulated current velocities with respect to
397 the OSCAR current velocities at the surface. However, due to coarse spatial resolution and lack of
398 consideration of shallow bathymetry in the computation of the current velocities, the OSCAR data
399 is unreliable for the comparative analysis of surface currents in the nearshore areas. Therefore, we
400 compare time-series data of in-situ surface current velocity measured by a subset of the CariCOOS
401 buoys moored near the coastline with the model outputs at the same locations (figure 3). Details on
402 the CariCOOS buoy data is discussed in section 4.4. For both the open ocean and nearshore analysis,
403 we do a comparison of the statistical variability of the surface currents using Taylor diagrams. For
404 the open ocean Taylor diagram, (i) the model outputs are re-mapped to the grid corresponding to
405 the OSCAR data; (ii) the OSCAR data and model outputs are flattened to 1-dimensional arrays by
406 concatenating all the time series of data at each and every grid point in the re-mapped domain. For the
407 nearshore analysis, we construct separate Taylor diagrams for the time series of the surface current
408 data at 4 different buoys at Ponce, San Juan, Vieques and St John respectively.

409 The temporal variability in the nearshore surface currents is further studied by comparing the
410 magnitude of the variance of the current velocities at different time scales using PSD plots of the
411 velocity variance from the buoy data compared with the model outputs at the same locations. We
412 study the PSD plots from 4 different CariCOOS buoys; Ponce, San Juan, Vieques and St John (figure
413 13).

414 **5.3 Surface Temperature Variability**

415 Marine biological production in the upper ocean is heavily influenced by the seasonal warming and
416 cooling of the surface boundary layer due to surface heat fluxes [Behrenfeld and Falkowski, 1997].
417 The summertime warming and wintertime cooling of the boundary layer had been noted in both
418 observations and numerical simulations [Behrenfeld and Falkowski, 1997, Behera et al., 2000]. Since
419 the SST is a good representative of the bulk temperature of the upper ocean boundary layer [Price
420 et al., 1986], a comparison of the seasonal variability of the modeled SST provides an insight on the
421 capability of the models to accurately represent the seasonal warming and cooling of the boundary
422 layer. We conduct two separate comparisons for the open ocean and nearshore SST variability. For
423 the open ocean, we (i) re-map the SST data from the model outputs to the G1SST domain, then (ii)
424 flatten the re-mapped data by concatenating the time arrays at each and every grid points in the re-
425 mapped domain. These flattened arrays are used to prepare a Taylor diagram to compare the standard
426 deviation, *RMSD* and cross-correlation of the model outputs with respect to the G1SST data in the
427 Caribbean Sea.

428 We further compare the open-ocean SST variability using a PSD plot of the model outputs and
429 the G1SST data. The PST plot for the SST is prepared as a function of the longitudinal wavenumber,
430 and is averaged over the full range of latitudes and sampling times in the data (figure 5).

431 For the nearshore analysis, we compare time series data of the temperature measured at the Cari-
432 COOS buoys and HOBO loggers located near the coastline with model outputs at the same locations.
433 The CariCOOS buoys measure the surface temperature, whereas the HOBO loggers measure benthic
434 temperature at nearshore coral reef sites. We evaluate the model performance by comparing prob-
435 ability density functions (PDF) of the model error, where the model error is the absolute value of
436 the difference between model output and the buoy data. The x-axis on the PDF plots denotes the
437 maximum value of each bin that corresponds to the range of error with a bin size of 0.1 units (figure

438 15,16). The y-axis in the PDF plots denotes the number of points lying within each error bin divided
439 by the total number of points in the time series. The relative performance of the model outputs is
440 determined by estimating which model has the highest percentage of points in the bin corresponding
441 to the lowest error.

442 To compare the seasonal variability of the benthic temperature in the nearshore regions, we select
443 three coral reef sites with the available HOBO logger data at Jacks Bay, Savana and St James (figure
444 3). We compare the temperature measurements at these sites with the model outputs at the same
445 locations using the PDF calculated from the errors in modeled temperature outputs (figure 16).

446 6 Results

447 Our analysis shows that in the open ocean regions of the US Caribbean, the cross-correlation of the
448 SSHA and surface currents between the model outputs and observed data is highest for the PSY4 and
449 lowest for the AMSEAS. The AMSEAS model, despite having a finer resolution, does not adequately
450 simulate the mesoscale flow in the open ocean regions. In the nearshore regions, none of the model
451 outputs show a strong correlation with the in-situ buoy measurements of the surface current velocities.
452 The SST from both the open-ocean and nearshore model outputs strongly correlate with the observed
453 data in terms of the seasonal variability. The results are discussed in detail below.

454 6.1 SSHA

455 Model performance of the SSHA variability is compared in the Caribbean Sea and along a meridional
456 transect in the Anegada Passage using two separate Taylor diagrams (figure 4a,4b) over a 1-year long
457 period in 2016. The Taylor diagram of the SSHA in the Caribbean Sea indicates that the highest
458 cross-correlation (0.81), lowest *RMSD* (0.59) and lowest standard deviation (0.08) between mod-
459 eled and observed SSHA were found for the PSY4. The AMSEAS and GOFS SSHA form similar
460 correlation coefficients of 0.65 and 0.62 with the AVISO respectively. The standard deviations of the
461 AMSEAS, GOFS and AVISO were 0.12, 0.11 and 0.08 respectively. One of the reasons for a larger
462 standard deviation between 2 models with the same resolution, is the implementation of a weaker
463 eddy viscosity which results in a stronger variance in the outputs [Ramachandran et al., 2013].

464 The contribution to the variance of SSHA by the processes associated with different spatial scales
465 is studied using a power spectral density (PSD) of the SSHA as a function of the wavenumber (figure
466 5). A comparison of the PSD of the SSHA at different spatial scales shows that within a range of
467 10 km to 100 km, the PSD of the AMSEAS SSHA has the highest magnitude, and is followed by
468 the PSD of the GOFS, PSY4 and the AVISO SSHA (figure 5). The AMSEAS SSHA also shows a
469 higher variance at scales larger than 100 km which is due to the combined influence of O(100 km)
470 mesoscale eddies and radially coherent baroclinic tides of wavelength in the range of 100 km to 180
471 km (figure 5) in the Caribbean Sea [Zaron, 2019]. The GOFS and PSY4 SSHA show a slightly higher
472 variance compared to the AVISO data at scales larger than 100 km, which is synonymous with the
473 higher peaks and deeper troughs of the mesoscale features in the GOFS and PSY4 outputs (figure 5a).
474 The PSD curve for the AMSEAS SSHA shows a slope of κ^{-3} (κ is the wavenumber) at spatial scales
475 near 100 km, but falls rapidly with a steeper slope at the lesser scales near 10 km. The slopes of the
476 GOFS and PSY4 PSD are close to κ^{-4} and the AVISO PSD shows the steepest slope larger than κ^{-4} .
477 The steeper slopes of the wavenumber spectra associated with the SSHA indicates the dominance
478 of mesoscale quasi-geostrophic turbulence and reduced influence of submesoscale turbulence in the
479 GOFS, PSY4 and AVISO SSHA [Callies and Ferrari, 2013]. Since the AMSEAS model can partially
480 resolve submesoscale features, it shows a relatively flatter slope in the SSHA PSD compared to GOFS,
481 PSY4 and the AVISO data.

482 In the Anegada Passage, standard deviations of the GOFS and PSY4 outputs from the AVISO
483 SSHA were nearly equal at 0.035 (figure 4b). The *RMSD* and cross-correlation of the GOFS with

respect to the AVISO were 0.0375 and 0.6 respectively. The AMSEAS correlated negatively with the AVISO and had the highest standard deviation (0.096) and *RMSD* (0.11), indicating a weaker performance for simulating SSHA in the Anegada passage. The performance of the PSY4 and GOFS models in the Anegada passage were similar. An analysis of the model performance along a zonal transect in the Anegada passage (plot not shown) showed that the AMSEAS SSHA correlated with the AVISO with a coefficient of 0.3, whereas the PSY4 and GOFS showed cross-correlation coefficients of 0.65 and 0.45 respectively. We infer from this analysis that changing the orientation of the transect in the Anegada passage alters the values of the statistical quantities, but does not affect the relative performance of the model outputs.

The SSHA contours in the plan view plots developed from the AVISO dataset shows prominent mesoscale features (figure 6). These notable mesoscale features in the AVISO data include the O (100 km) cyclonic eddy on 16th March at the southern edge of the contour plot within latitudes 13.5^0 - 15^0 N; the O(100 km) anti-cyclonic eddy near the southern edge within latitudes 13.5^0 - 15^0 N on 13th June and the O(100 km) cyclonic eddy near the southern edge within latitudes 13.5^0 - 15^0 N on 17th October (figure 6). The clear display of these features in the three model outputs indicates the likelihood that the GOFS, PSY4 and AMSEAS resolve most mesoscale features observed in the open-ocean regions of the Caribbean sea observed in the AVISO dataset. Apart from these mesoscale features, the SSHA from the AMSEAS output also shows O(10 km) small-scale meanders which are absent in the GOFS, PSY4 and AVISO. These small-scale features are a consequence of finer grid resolution and weaker eddy viscosity that permits instabilities at scales finer than the mesoscale spatial range [Ramachandran et al., 2013].

Apart from the O(100 km) mesoscale eddies and O(10 km) small-scale undulations in the AMSEAS SSHA, we also observe radially propagating ripples that appear to originate from the south-east vertex of the domain. These ripples are internal baroclinic tides propagating radially outward from the Aves Escarpment (latitude 13^0 N longitude 62^0 W), which is a mid-ocean ridge in the Caribbean Sea to the west of the lower Antilles islands (figure 1). During the periodic flow of tidal currents over the steep topography of the Aves ridge, vertical oscillation of the isopycnal surfaces of the stratified ocean leads to the formation of baroclinic tides [Jithin et al., 2020]. Ripples formed by baroclinic tides at the Aves ridge have been observed on the sea surface in images captured by the MODIS Terra and Aqua satellites during sun-glint conditions [Alfonso-Sosa, 2013]. Due to the implementation of the OTIS tidal package in the AMSEAS model framework, such baroclinic tidal ripples propagating from the Aves ridge are also simulated by the AMSEAS model in the Caribbean Sea [Zaron, 2019]. Since the GOFS and PSY4 do not implement tidal forcing, we do not observe such baroclinic tidal ripples in their outputs.

A Hovmöller diagram of the AVISO SSHA along the transect shows a consistently positive meridional gradient in the SSHA from May to December 2016 for the GOFS and PSY4 outputs. This same positive trend, however, does not appear in the Hovmöller diagram of the AMSEAS output (figure 7). The model outputs also show small-scale temporal fluctuations in the SSHA that correspond to a stronger variance compared to the AVISO at frequencies higher than $1/10$ day $^{-1}$, as shown in the temporal power spectral density (PSD) plot (figure 8). The PSY4 SSHA variance is weaker in magnitude than the GOFS and AMSEAS at frequencies higher than $1/10$ day $^{-1}$, which is due to the combined influence of stronger eddy viscosity and the coarser resolution of the PSY4 model for the US Caribbean region [Ramachandran et al., 2013]. The variance in the SSHA from the AMSEAS also shows prominent tidal maxima at the diurnal (S1 and K1) and semi-diurnal (M2 and S2) frequencies. The GOFS and PSY4 do not show similar tidal maxima due to the lack of tidal forcing implemented in their simulations.

530 **6.1.1 Analysis using Okubo-Weiss parameter**

531 The mesoscale eddy variability from the model outputs is compared with that from the AVISO data
532 using the Okubo-Weiss parameters derived from the SSHA (figure 9). Since the AMSEAS SSHA
533 are contaminated with internal tidal oscillations (figure 6), we remove the tidal oscillations and the
534 small-scale processes by using a 2-dimensional spatial lowpass filter with a cutoff wavenumber of
535 $1/30 \text{ km}^{-1}$. The GOFS and PSY4 SSHA does not require filtering since they do not implement a tidal
536 model.

537 Notable mesoscale features in the AVISO contour plots (figure 9) are a cyclonic eddy within
538 latitudes $13.5^{\circ} - 15^{\circ}$ N surrounded by a strain field on 16th March, an anti-cyclonic eddy near the
539 southern edge within latitudes $13.5^{\circ} - 15^{\circ}$ N surrounded by a strain field on 13th June, and a cyclonic
540 eddy near the southern edge within latitudes $14^{\circ} - 15^{\circ}$ N on 17th October and a cyclonic eddy near
541 the northwest vertex on 14th December. These mesoscale structures also appear in the PSY4 and
542 GOFS model outputs of the Okubo-Weiss parameter. The lowpassed AMSEAS outputs also show the
543 large anti-cyclonic eddy at 13th June and the cyclonic eddy at 16th March. However, the mesoscale
544 features appearing during 17th October and 14th December in the lowpassed AMSEAS SSHA, do not
545 match with the AVISO data in terms of their locations. The contrast in the variability of the mesoscale
546 eddies in the AMSEAS and the AVISO outputs, could be attributed to the fact that small-scale features
547 permitted by the AMSEAS model's fine resolution deteriorates the simulated mesoscale variability
548 [Sandery and Sakov, 2017].

549 **6.2 Surface Current Velocities**

550 We conduct two separate comparisons for the model performance in terms of simulating the surface
551 currents in the open ocean and the nearshore regions of the US Caribbean ocean.

552 **6.2.1 Open Ocean Current Velocity**

553 Model performance is evaluated regarding the surface current velocity in the OSCAR data using Tay-
554 lor diagrams to compare the correlation coefficients, $RMSD$ and standard deviation of the model
555 outputs with respect to the OSCAR data in the open-ocean regions of the Caribbean sea for 2016.
556 Taylor diagrams for the open-ocean outputs (figure 10) shows that the highest cross-correlation (0.74
557 for both zonal and meridional velocities), and the lowest $RMSD$ (0.1 for zonal and meridional veloc-
558 ities respectively) with the OSCAR velocity data were found for the PSY4 (figure 10). The standard
559 deviation between the PSY4 model outputs and the OSCAR data is the lowest among the three model
560 frameworks (0.2 for the zonal and meridional velocities). The AMSEAS output correlates well with
561 the OSCAR data for the zonal velocity with a coefficient of 0.65 but shows a very weak correlation for
562 the meridional velocity with a coefficient of 0.03 (figure 10b). The cross-correlation coefficient be-
563 tween the GOFS and OSCAR data is 0.7 and 0.6 for the zonal and meridional velocities respectively,
564 which lie between the PSY4 and AMSEAS coefficients in terms of their magnitude.

565 The zonal velocity in the open-ocean regions of the Caribbean sea mostly represents the westward
566 flow of the Caribbean current forced by the inflow of the Atlantic water through the passages between
567 the Antilles islands. The meridional velocity in the Caribbean Sea observed in the model outputs and
568 OSCAR data is representative of the meridional deviation of the westward Caribbean current due to
569 mesoscale and submesoscale turbulence. In the Hovmöller diagram in figure 11, the Caribbean current
570 is observed as a continuous westward flow in the model outputs, with a short-lived eastward flow that
571 arises by the transit of the mesoscale eddies through the domain between the days 150 to 250. The
572 contrast between the correlation of the AMSEAS zonal and meridional velocities, when compared
573 with the OSCAR data, suggests that the AMSEAS model under-performs in the representation of the
574 meridional currents in the Caribbean Sea.

575 The PSD of the AMSEAS current velocities (figure 5b) show a typical slope of κ^{-3} which is
576 flatter than the GOFS, PSY4 and OSCAR data. The GOFS and PSY4 outputs show a typical slope of
577 κ^{-4} , whereas the OSCAR velocities show a slope steeper than κ^{-4} . In the presence of submesoscale
578 turbulence, we typically observe a slope of κ^{-2} in the momentum and tracer variances provided the
579 spatial resolution of the measurement is sufficiently high to capture submesoscale turbulence over a
580 spatial scale of 500 m to O(10 km) [Callies and Ferrari, 2013, Brannigan et al., 2015]. The κ^{-3} slope
581 of the AMSEAS current velocities indicate that the AMSEAS only partially resolves the submesoscale
582 turbulence in terms of the current velocities. The 10 km resolution in the GOFS and PSY4 models
583 make it impossible for them to resolve submesoscale turbulence, which explains the steeper slopes in
584 the velocity variance PSD from these models.

585 **6.2.2 Nearshore Current Velocity**

586 Analysis of the Taylor diagrams for the nearshore surface current velocities at the Ponce, San Juan, St.
587 John and Vieques CariCOOS buoys shows that all the model outputs correlate very weakly with the
588 buoy data; cross-correlation coefficients range from -0.2 to 0.45 (figure 12). The AMSEAS current
589 outputs demonstrate larger values of *RMSD* and larger standard deviation compared to the GOFS
590 and PSY4 outputs which show nearly similar values of the *RMSD* and standard deviation. A weak
591 correlation coefficient between the modeled current outputs and the OSCAR current data indicates
592 that none of the model outputs exhibit a realistic performance near the coastlines, which is expected
593 given the incapability of the model resolutions to realistically represent the coastal bathymetry.

594 A temporal power spectral density (PSD) of the eddy kinetic energy (EKE), which displays the
595 variance of the current velocities at the 4 buoy locations, indicates that within a range of $\omega = 10^{-2} -$
596 10^0 day^{-1} (ω is the inverse of the time period), the EKE decays by a factor of approximately ω^{-1} for
597 both the buoy data as well as the model outputs (figure 13), which is similar to the decay shown by
598 HF-radar derived observations of the current velocities on the US west coast [Kim et al., 2011]. At
599 frequencies larger than the inertial frequency, the PSY4 and GOFS outputs demonstrate a steeper rate
600 of decay due to the inability of these models to represent the variance corresponding to small-scale
601 variability spawned by gravity-wave dynamics and 3D turbulence [Ferrari and Wunsch, 2009]. In
602 contrast, the AMSEAS shows a slope of ω^{-1} at frequencies larger than the inertial frequency because
603 the finer resolution of the AMSEAS model framework permits small-scale variability in the velocity
604 fields that are absent in the other two model outputs.

605 **6.3 Temperature Variability**

606 **6.3.1 Seasonal SST Variability in the open ocean**

607 The open-ocean SST variability in the US Caribbean is compared with respect to the G1SST data
608 from 2016. The cross-correlation coefficients ranging from 0.89 to 0.91 between each of the model
609 SST outputs and the G1SST data indicates that the seasonal SST variability in the models is strongly
610 correlated with that of the observed data in the Caribbean Sea (figure 14). The *RMSD* of all the
611 model SST outputs are 0.4 with respect to the G1SST, and the standard deviation is nearly 0.8.

612 The strong correlation of the simulated SST indicates that all the models perform reasonably well
613 in simulating the seasonal variability of the SST in the Caribbean Sea.

614 **6.3.2 Spectral SST variability**

615 The PSD of SST obtained from the G1SST data varies with a slope of κ^{-2} (figure 5c) near the spatial
616 scale of 100 km, but becomes steeper with a slope of κ^{-3} near the 10 km spatial scale. A tracer
617 spectral slope of κ^{-2} indicates that submesoscale turbulence is the prime contributor to the surface
618 variance of the tracer [Brannigan et al., 2015, Castro et al., 2017]. Due to the fine resolution of

619 3 km in the AMSEAS model, the AMSEAS SST output showed a typical spectral slope of κ^{-2}
620 (figure 5c) which indicates that submesoscale turbulence strongly dominates the surface variance of
621 the AMSEAS temperature outputs. The GOFS and PSY4 SST outputs show a typical spectral slope of
622 κ^{-3} which is an indicative of the SST variance being dominated by quasi-geostrophic 2D turbulence
623 associated with mesoscale eddies [Callies and Ferrari, 2013].

624 6.3.3 Nearshore SST Variability

625 The temperature measurements from the CariCOOS buoys along the northern coastline of PR shows
626 a pattern of annual wintertime cooling from January to March, followed by summertime warming
627 between March and October due to the seasonal variability in the shortwave radiation. A comparison
628 of the temperature time series in 2016 shows that the seasonal variability in the SST seen in the buoy
629 data is clearly replicated by all the model outputs (figure 15).

630 Figures 15e–h show the PDF of the model error at the 4 different CariCOOS buoy locations
631 (Ponce, San Juan, St John and Vieques). The x-axis denotes the maximum value of each bin corre-
632 sponding to the range of error with a bin size of 0.1 units. At the St John, Vieques and Ponce buoys,
633 the PSY4 shows the highest percentage of points (54%, 52%, 34%) lying within the bin correspond-
634 ing to the lowest level of error which is 0.1. At an intermediate error range of 0.5 to 0.9, the PSY4
635 shows the lowest percentage of points. At the San Juan buoy, the AMSEAS shows better results with
636 the highest percentage of points (30%) within the 0.1 error bin, and the lowest percentage of points at
637 between the 0.7–0.9 error bins.

638 The temperature time series plots from the HOBO loggers at the coral reef sites show similar
639 summer warming and winter cooling patterns (figure 16a,c,e) as the temperature data recorded at the
640 CariCOOS buoys (figure 15). This similarity between the CariCOOS buoy and HOBO logger datasets
641 is because the shallow depths of the coral reef sites at Jacks Bay, Savanna and St James (14 m, 9 m
642 and 15 m) are within the upper ocean boundary layer where there is a strong response to the seasonal
643 variability of the atmospheric heat fluxes. The simulated temperature from the model outputs at the
644 corresponding coral reef locations also show a similar seasonal variability (figure 16a,c,e). The PDF
645 plot of the model errors shows that at Jacks Bay and St James, the AMSEAS forms a higher fraction
646 of points (0.24 and 0.26 respectively) corresponding to the lowest error bin, whereas at Savana the
647 GOFS forms a higher fraction of points (0.21) at the same bin (figure 16b,d,f).

648 7 Discussion

649 This work explores the strengths and weaknesses of the currently operational ocean model frame-
650 works specific to the US Caribbean coastal ocean: the GOFS at $1/12^0$ resolution, the PSY4 at $1/12^0$
651 resolution and the AMSEAS at $1/36^0$ resolution. The GOFS and AMSEAS use the NCODA, and
652 the PSY4 uses the SEEK filter for assimilating observed data to the outputs. We conduct a series of
653 comparative analysis of the simulated ocean properties from these model frameworks with the corre-
654 sponding observational data for the Caribbean Sea, which includes the SSHA from AVISO satellite
655 altimetry, surface current velocities from the OSCAR, and interpolated surface temperature estimates
656 by the G1SST from various satellite measurements. While these observational datasets are also avail-
657 able for the coastal ocean surrounding Puerto Rico and the Virgin Islands, the coarse resolution of
658 the data around the islands makes them less reliable for representing the nearshore ocean properties.
659 Therefore, we compared the simulated nearshore temperature and current velocities with in-situ time
660 series data of the temperature and velocities measured at the moored buoys operated by CariCOOS,
661 and time series of temperature measurements using HOBO loggers. All the observed satellite and
662 in-situ data and model outputs used in our analysis are from the year 2016.

663 In the open ocean regions of the Caribbean Sea, lowest *RMSD* and highest cross-correlation of
664 the PSY4 outputs with respect to the observed data suggests that the PSY4 produces the most realistic

665 representation of the mesoscale variability in the SSHA. The GOFS model also produces realistic
666 outputs, but with a slightly weaker correlation coefficient and a slightly larger variance than the PSY4
667 outputs due to the implementation of a weaker eddy viscosity. The temporal variability of the PSY4
668 SSHA along the transects in the Anegada passage, are also the most realistic compared to the other
669 model outputs. The AMSEAS model produces realistic open-ocean outputs of the SSHA and the
670 zonal current velocities, but fails to produce a realistic SSHA output in the Anegada passage.

671 In terms of the open-ocean surface current velocities, the PSY4 and GOFS produce the most real-
672 istic outputs when compared to the OSCAR data, with the PSY4 showing slightly higher correlation
673 coefficients than the GOFS. The zonal currents in the OSCAR data are majorly dominated by the
674 westward flowing Caribbean current, which is realistically simulated by all the models. However,
675 the AMSEAS model fails to realistically simulate the meridional currents which are formed by the
676 meridional deviation of the Caribbean current due to submesoscale and quasi-geostrophic mesoscale
677 turbulence.

678 The under-performance of the AMSEAS model in the open-ocean regions of the Caribbean sea,
679 despite it's fine resolution, is attributed to the following reasons:

- 680 • The AMSEAS model only partially resolves submesoscale turbulence, and is therefore inade-
681 quate to represent the full spectrum of submesoscale turbulence which spans over a range of
682 spatial scales from 500 m to O(10 km).
- 683 • The NCODA data assimilation system, used by the AMSEAS, is tuned to constrain the model
684 outputs towards the observed data on the order of spatial scales equivalent to or larger than the
685 mesoscales [Carrier et al., 2019], and is therefore not effective on the submesoscale character-
686 istics of the flow.
- 687 • There are no realistic submesoscale variability in the gridded observed data assimilated by the
688 NCODA due to coarse resolution.
- 689 • Submesoscale turbulence permitted by the AMSEAS model's fine resolution deteriorates the
690 model output's mesoscale variability due to inverse energy cascade associated with the subme-
691 soscales [Sandery and Sakov, 2017].

692 Since the GOFS, AMSEAS and PSY4 models assimilate observed data, the inferences drawn from
693 the comparative analysis are also an indicative of the performance of the data assimilation algorithms
694 used by the model frameworks. We infer from our analysis that for a numerical grid capable of
695 resolving only the mesoscales and larger scales, both the NCODA and the SEEK filter produce similar
696 outputs. The difference of the variance of outputs between the 2 models with the same resolution,
697 depends on the strength of the eddy viscosity used by the models. Since the NCODA is tuned to
698 constrain the model outputs only at the order of the mesoscales, it is ineffective on the submesoscale
699 turbulence generated by the AMSEAS model at a finer resolution of 3 km. Due to inverse energy
700 cascade, the submesoscale turbulence tends to alter the mesoscale variability in the AMSEAS outputs,
701 thus adversely affecting the performance of the AMSEAS model at O(100 km) mesoscales. However,
702 the strongly dominating Caribbean current in the simulated zonal velocity of the AMSEAS model
703 does not appear to be affected by the interference of the submesoscale turbulence. Therefore, the
704 AMSEAS under-performs in terms of the SSHA and the meridional velocities, but produces a realistic
705 simulation of the Caribbean current associated with the zonal velocities.

706 The nearshore surface current velocities from all the model outputs correlate very weakly with
707 the in-situ measured velocities from the buoys, which is expected given the coarse resolution of the
708 models. The seasonal variability of the surface temperature and benthic temperature, however, is well
709 represented by all the model outputs in the open ocean and the nearshore regions, as is evident from
710 the strong correlation of the modeled SST with the observed G1SST data. The realistic representation
711 of the seasonal SST variability in both the nearshore and open ocean regions occurs largely as a
712 response of the surface boundary layer to the seasonal variability in the atmospheric heat flux due to
713 shortwave radiation [Price et al., 1986]. Since the impact of the shortwave radiation on the surface

714 boundary layer is well simulated by the GOFS, AMSEAS and PSY4 models using different vertical
715 mixing parameterizations, they are all capable of representing the seasonal SST variability at both the
716 nearshore and the open-ocean regions.

717 Various oceanic applications require realistic estimates of the ocean properties. A comparative
718 analysis of the model performance is necessary to determine which model output is the most suitable
719 for a specific application that requires oceanographic data. Based on our study, the PSY4 outputs
720 are the more suitable for those applications that require realistic estimates of the open-ocean surface
721 current velocities and the SSHA, whereas any of the PSY4, GOFS and AMSEAS outputs can be used
722 for applications that require data on the seasonal temperature variability. For example, to determine
723 the optimum route for ship navigation in the US Caribbean ocean, the user can refer to the PSY4
724 outputs for the most realistic estimates of the surface currents and SSHA; to study the impact of
725 seasonal warming on coral bleaching, marine ecologists can refer to any of the GOFS, AMSEAS
726 and PSY4 model outputs for realistic estimates of the benthic temperature; the fisheries industry in
727 the US Caribbean regions can refer to the PSY4 outputs to know the location and trajectories of the
728 mesoscale eddies and determine the potential areas with high chlorophyll concentration.

729 Applications related to marine ecology mostly require nearshore data of the ocean properties; sim-
730 ulating the larval and sediment transport requires nearshore current velocity data; studying the impact
731 of the seasonal temperature changes on coral reef resilience requires data of the nearshore benthic
732 temperature variability at the coral reef sites. It is clear from our analysis that while the nearshore
733 temperature variability outputs from all the models are reliable, the nearshore current velocity data
734 from any of the models are not realistic enough to be useful. Therefore, the necessity to develop a fine
735 resolution modeling system for the Puerto Rico and the US Virgin Islands coastal ocean circulation
736 motivates further research. A fine resolution model that uses the PSY4 open ocean outputs as bound-
737 ary conditions, the nearshore buoy measurements for assimilation, and surface forcing from a state of
738 the art atmospheric model, can be useful for the marine ecological applications in the US Caribbean
739 ocean.

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744 Chérubin at Florida Atlantic University for their valuable insight.

Table 1: Forecast system model parameters

	GOFS	AMSEAS	PSY4
Model	Hybrid Coordinate Ocean Model (HYCOM)	Navy Coastal Ocean Model (NCOM)	Nucleus for European Modelling of the Ocean (NEMO)
Horizontal grid	Orthogonal curvilinear ($1/12^0$)	Orthogonal curvilinear ($1/36^0$)	Triangular (12 0) ORCA
Vertical grid	32 levels, (isopycnal in open ocean, terrain following in coastal ocean, z-level in mixed-layer)	40 levels, terrain-following σ coordinates near surface and z-level coordinates below	50 levels, decreasing resolution from 1 m at the surface to 450 m at bottom, 22 levels within upper 100 m.
Advection	multi-dimensional positive advection transport [Smolarkiewicz and Grabowski, 1990]	quasi-third order upwind advection for momentum and scalars [Holland et al., 1998]	energy/enstrophy conserving scheme (momentum) [Arakawa and Lamb, 1981], TVD 2nd order scheme (tracer) [Lévy et al., 2001]
Mixing	2nd order Flux Corrected Transport (FCT) [Zalesak, 1979] (horizontal eddy viscosity 50 m^2s^{-1}), KPP for vertical mixing	Mellor-Yamada 2.5 vertical mixing, Smagorinsky scheme [Smagorinsky, 1963] for horizontal viscosities	Laplacian isopycnal (tracer) ($80 \text{ m}^2\text{s}^{-1}$), biharmonic (momentum) ($-1 \times 10^{11} \text{ m}^4\text{s}^{-1}$), turbulence closure 1.5 [Blanke and Delecluse, 1993]
Surface forcing	NAVGEM	15 km Navy COAMPS model	ECMWF
Data assimilation	NCODA with 3DVAR	NCODA with 3DVAR	SAM (reduced-order Kalman filter) with 3DVAR
Data assimilated	SSH anomaly (AVISO), SST (GHRSSST), in-situ observations from ships, buoys, XBT, CTD, Argo floats,	same as GOFS	CMEMS (OSTIA SST, sea-ice concentration and SSH), WOA 2013 climatology below 2000 m
Sampling time	3-hourly instantaneous	3-hourly instantaneous	1-hourly instantaneous

Table 2: Gridded ocean datasets

	AVISO	OSCAR	GHRSST
Ocean property	Sea-surface height anomaly (m) (SSHA)	Surface current velocities (m/s)	Sea-surface temperature (SST) ($^{\circ}$ C)
Horizontal Grid	1/4 $^{\circ}$ of latitude	1/3 $^{\circ}$ of latitude	1 km
source of data	Altimetry measurements from altimeters aboard the TOPEX/Poseidon, Envisat, Jason-1 and OSTM/Jason-2	Interpolation and analysis of SSHA, surface wind velocity and SST data obtained from satellite and in-situ measurements	AVHRR, AATSR, SEVIRI, AMSRE, TMI, MODIS, GOES, MTSAT-1R
Temporal averaging	daily averaged	averaged over 5 days	daily averaged

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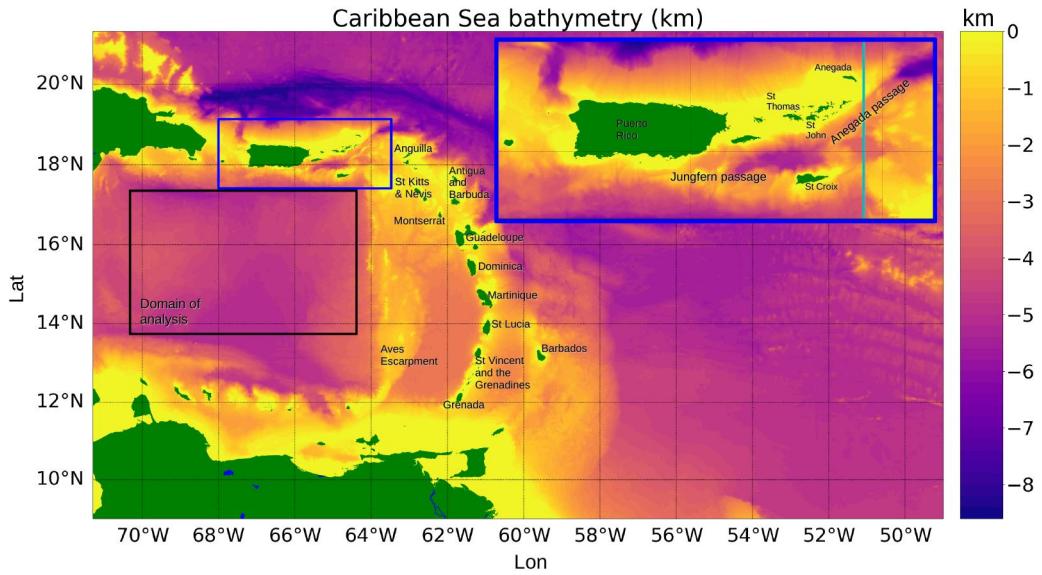


Figure 1: Bathymetry of the northern Caribbean Sea from ETOPO 1 km. Landmasses are denoted by green color. The black rectangle denotes the region where we do the comparative analysis between model outputs. The blue rectangle denotes the domain containing Puerto Rico and the Virgin Islands, and is enlarged to show the islands and Anegrada passage in detail.

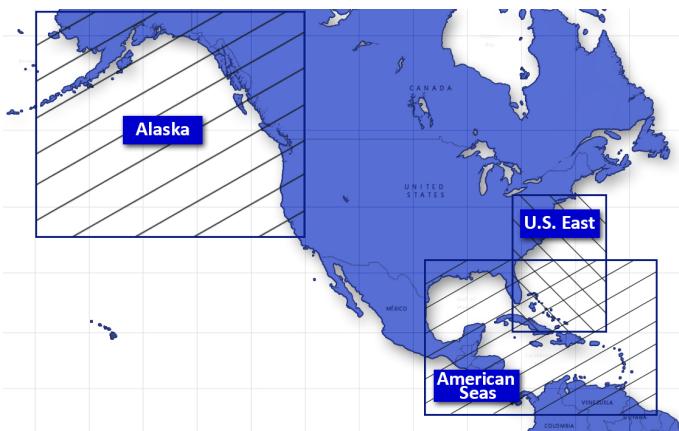


Figure 2: Map showing the regional grids for Alaskan Sea, US East Coast, and Gulf and Mexico and Caribbean Sea covered by the NCOM model. This map is obtained from the NOAA NCOM server.

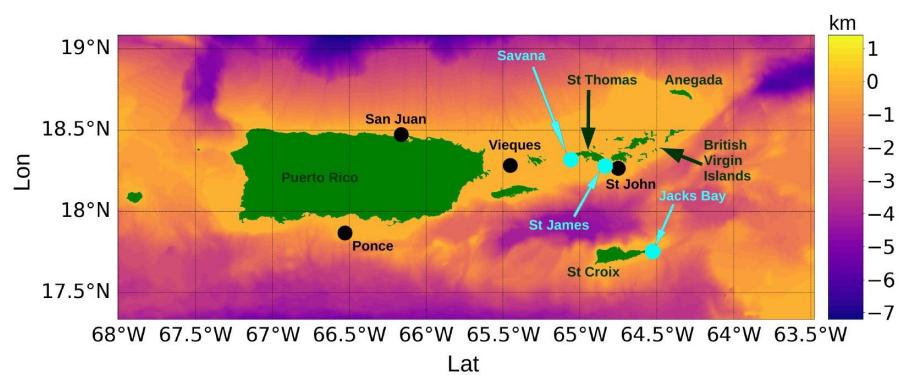


Figure 3: ETOPO 1 km bathymetry of the Puerto Rico and Virgin Islands coastal ocean, with filled circles showing the locations of the CariCOOS buoys (black) at Ponce, San Juan, Vieques, St John, and the TCRMP coral reef sites (indigo) at Jacks Bay, Savanna and St James. The CariCOOS buoys provide in-situ surface currents, and the HOBO loggers at the TCRMP sites provide benthic temperature data.

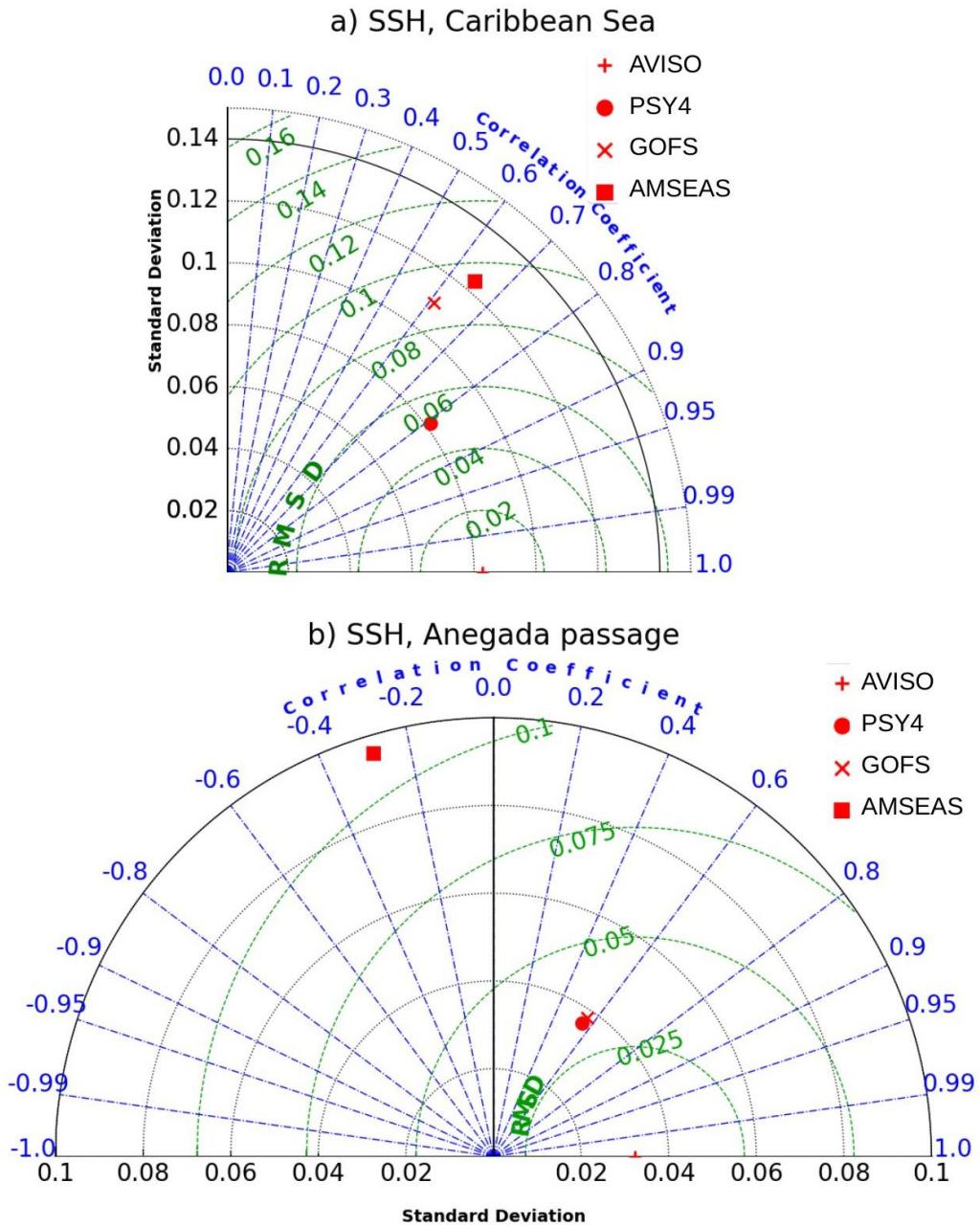


Figure 4: Taylor diagram of the SSHA from the AVISO and the PSY4, GOFS and AMSEAS model outputs in 2016 for Caribbean Sea (plot a), and along a meridional transect in the Anegada passage (plot b). The length along the radial axis denotes the standard deviation. The arc length along the circumference denotes the cross-correlation coefficient of each model output with the AVISO dataset. The model outputs and the AVISO dataset are represented by different markers on each plot. The AVISO marker lies on the x axis, and the length of each model's marker to the AVISO marker denotes the *RMSD*.

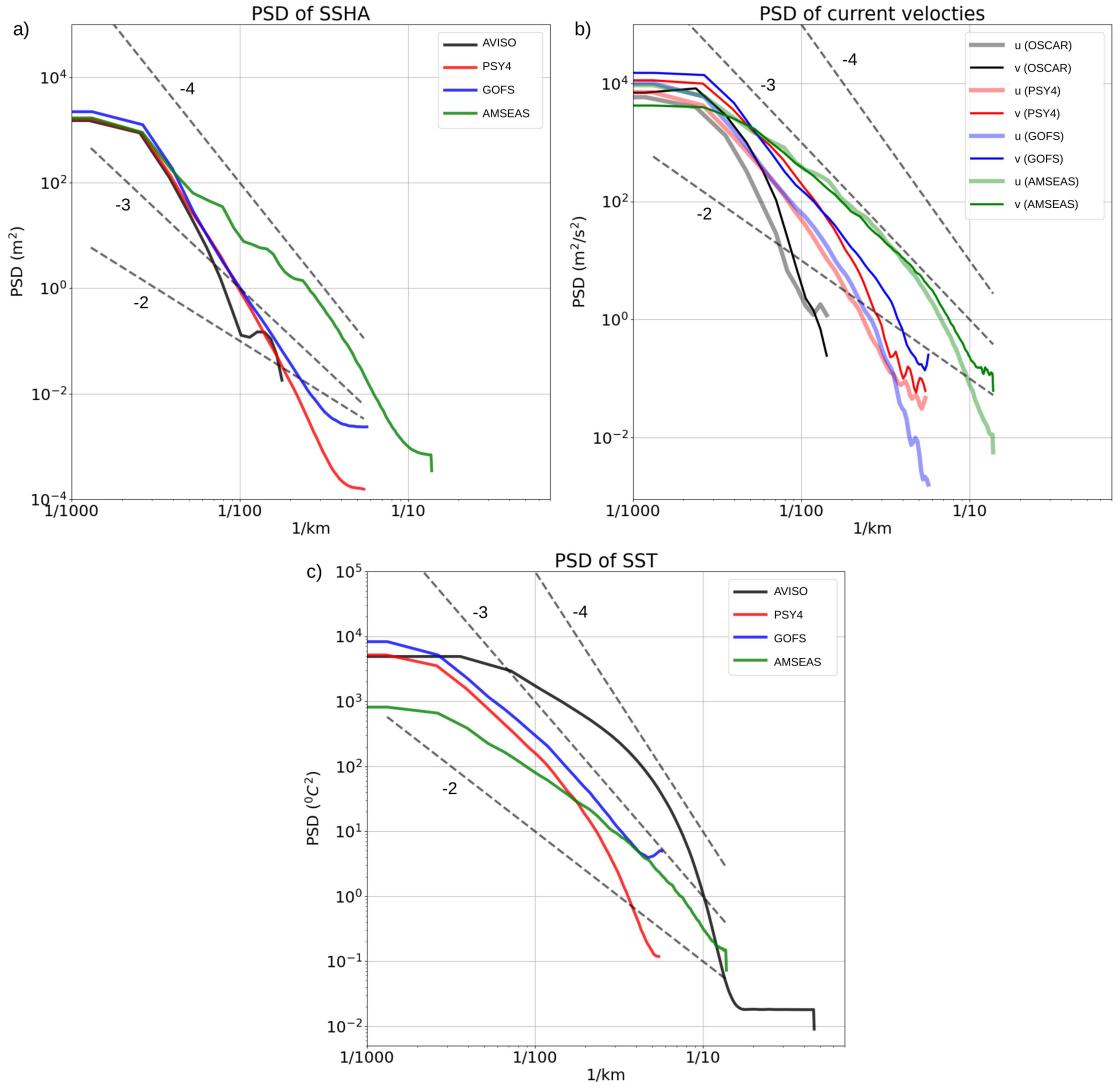


Figure 5: Spatial power spectral density (PSD) of the SSHA (plot a), surface current velocities (plot b) and SST (plot c) of the model outputs compared to the AVISO SSHA, OSCAR current velocities and G1SST temperature respectively. The dashed lines denote the slopes of κ^{-4} , κ^{-3} and κ^{-2} on the loglog plot (κ is the wavenumber).

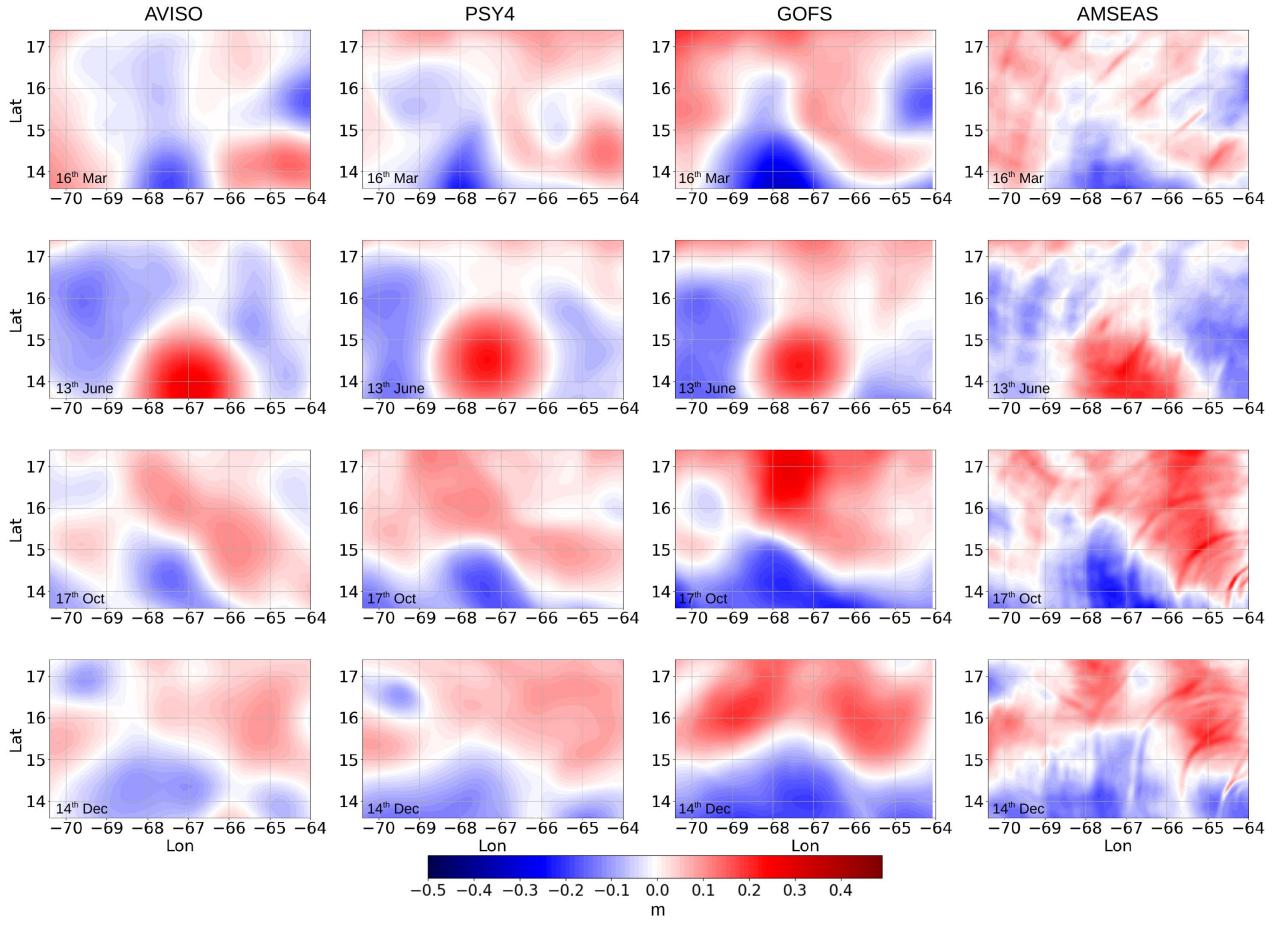


Figure 6: Contour plots showing the sea-surface height anomaly (SSHA) from the AVISO altimetry data and the PSY4, GOFS and AMSEAS models in the Caribbean Sea at 4 randomly chosen dates in 2016. The columns from left to right show the SSHA from the AVISO, PSY4, GOFS and AMSEAS respectively. The rows from top to bottom show the SSHA from the dates 16th March, 13th June, 17th October and 14th December respectively.

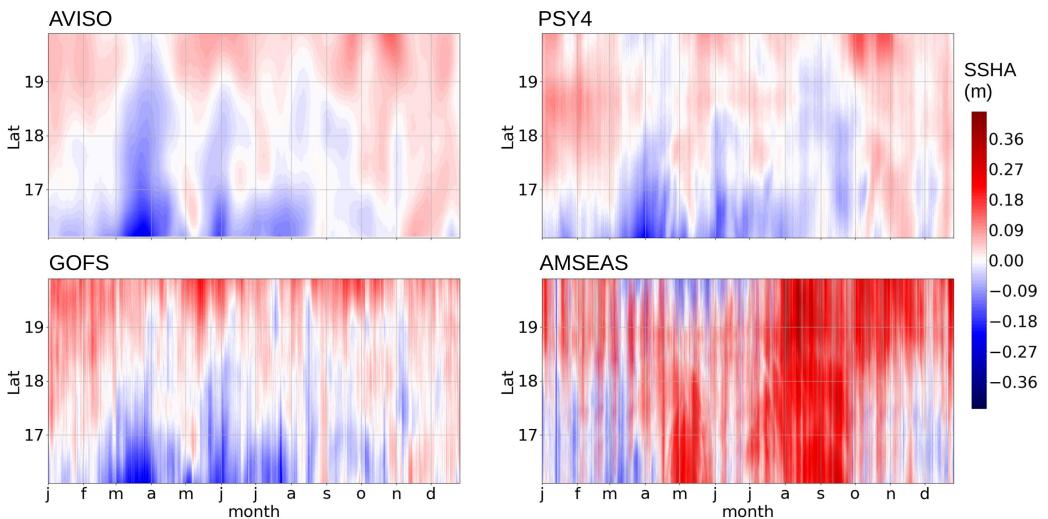


Figure 7: Hovmöller diagram showing the temporal variability of the SSHA from the (a) AVISO, (b) PSY4, (c) GOFS and (d) AMSEAS in 2016 along a meridional transect in the Anegada passage on the east of St John island at longitude 64.2° W. The meridional transect is denoted in figure 1 by the indigo line.

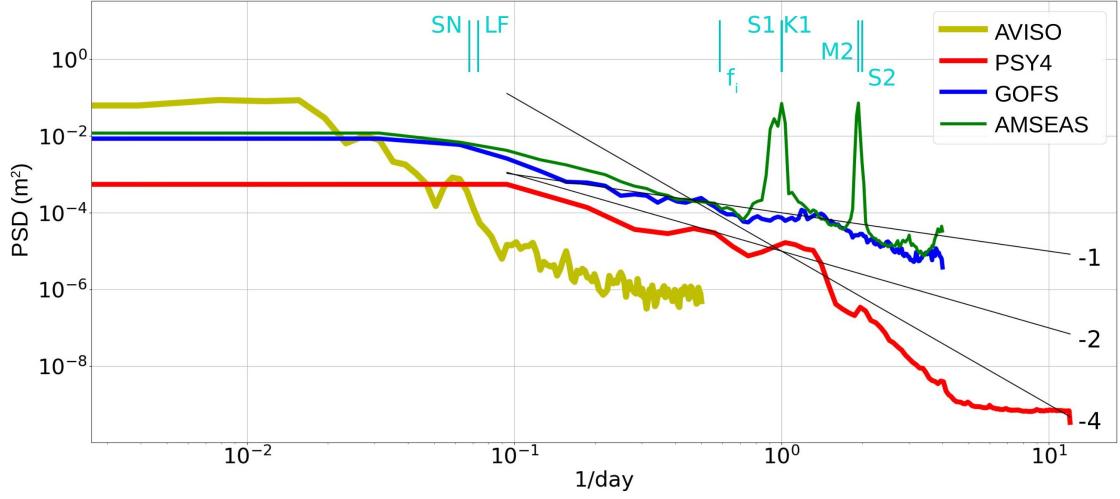


Figure 8: Average power spectral density (PSD) of the time series of the SSHA along a meridional transect in the Anegada passage at latitude 18^0 N. The averaging is done over the range of longitudes from 16^0 to 20^0 N. The tidal frequencies for diurnal (S1, K1) and semi-diurnal (M2, S2) tides are marked in cyan. The variable f_i denotes the inertial frequency corresponding to 40 hours.

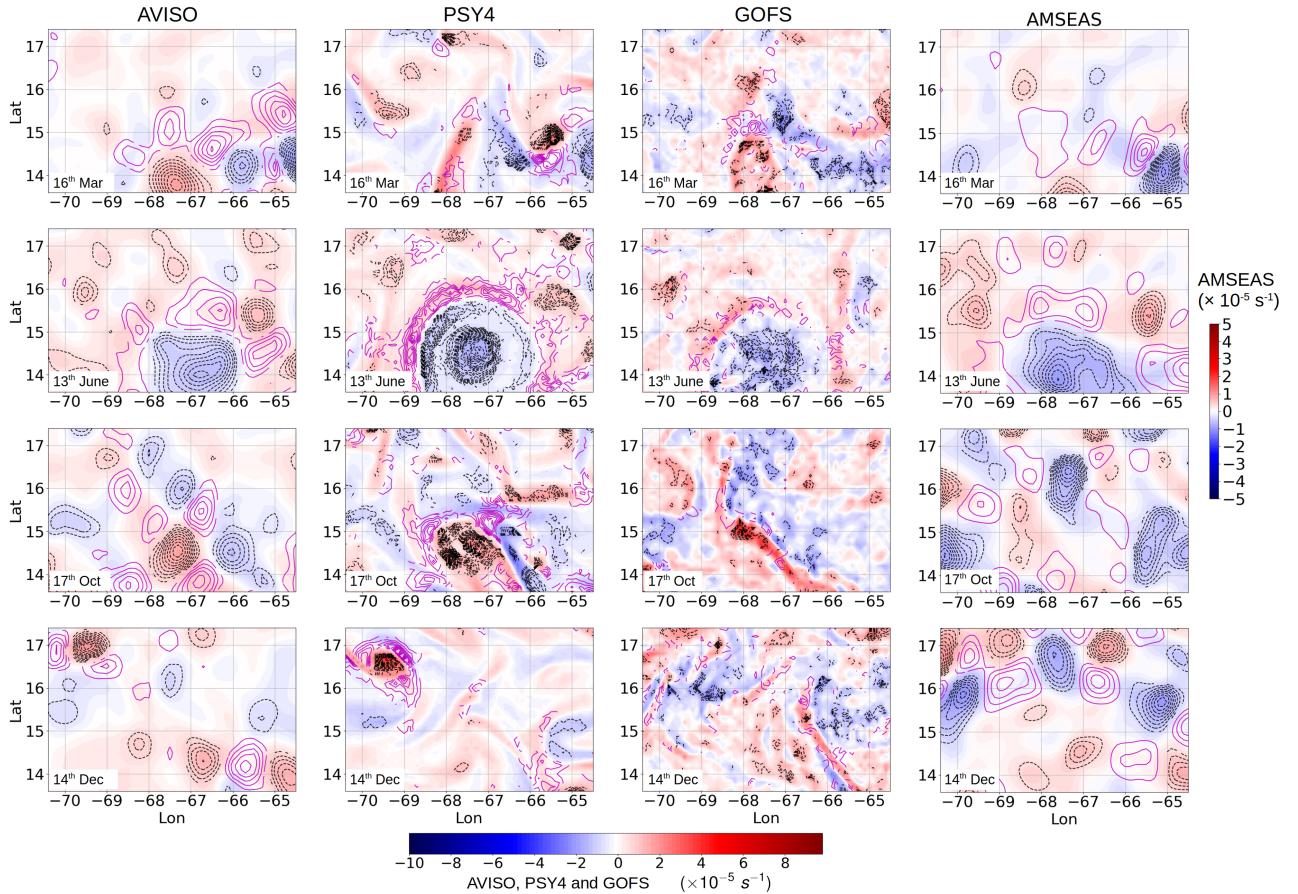


Figure 9: Plan view plots showing the relative vorticity (ζ s^{-1}) in red and blue color and the Okubo-Weiss parameter in black and magenta contour lines. The dashed black lines show the regions where $W < -0.2\sigma$ where σ is the standard deviation of W corresponding to the same sign of the relative vorticity ζ . The solid magenta lines show the regions where $W > 0.2\sigma_W$. From top to bottom, the rows show the contours on 16th March, 13th June, 17th October and 14th December 2016 respectively. The lowpassed AMSEAS contours are shown with a different color scale to highlight the oceanographic features prominently.

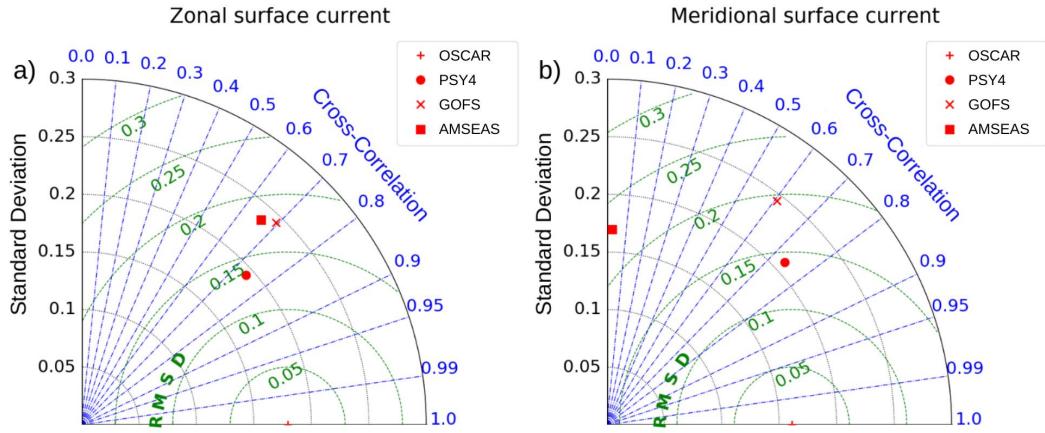


Figure 10: Taylor diagrams of the simulated surface currents from the PSY4, GOFS and AMSEAS with respect to the OSCAR dataset in 2016. Plot a is calculated from the zonal surface currents and plot b from the meridional surface currents. Current velocity from each model output and the OSCAR data are represented by different markers. The radial axis denotes the standard deviation and the azimuthal axis the cross-correlation coefficient. The length of each marker from the OSCAR marker denotes the RMSD.

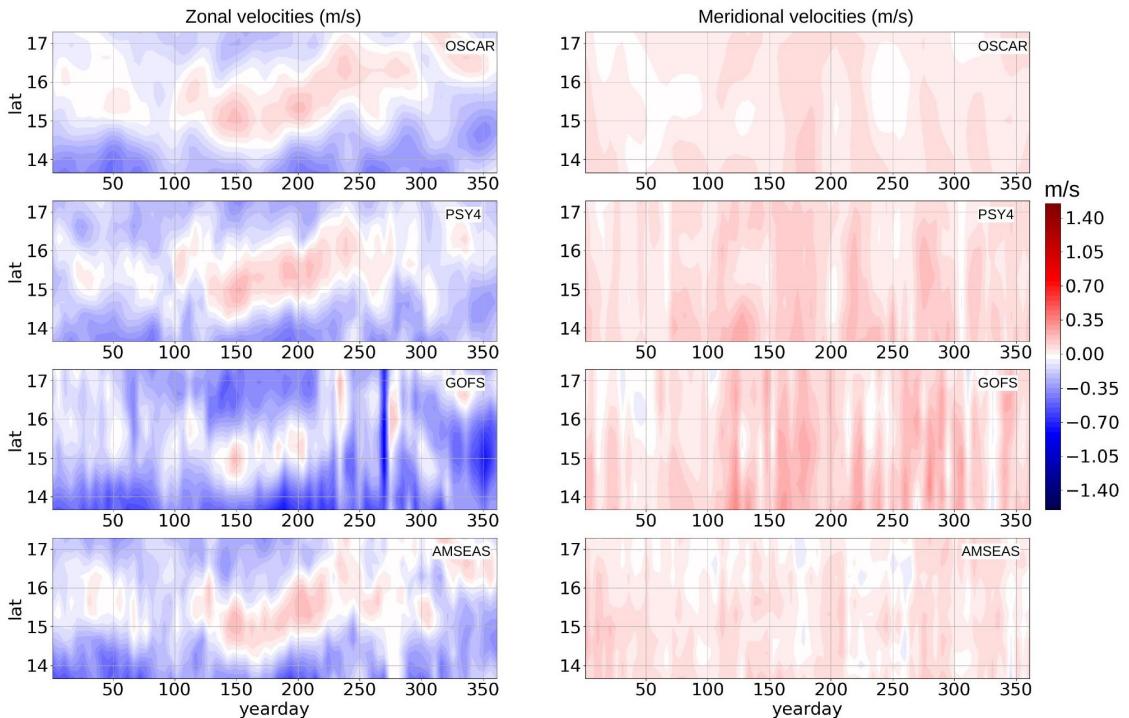


Figure 11: Hovmöller diagrams showing the zonal and meridional velocities from the model outputs and the OSCAR data over a span of 1 year in 2016, averaged over the longitudes. The left and right panels show the zonal and meridional velocities respectively.

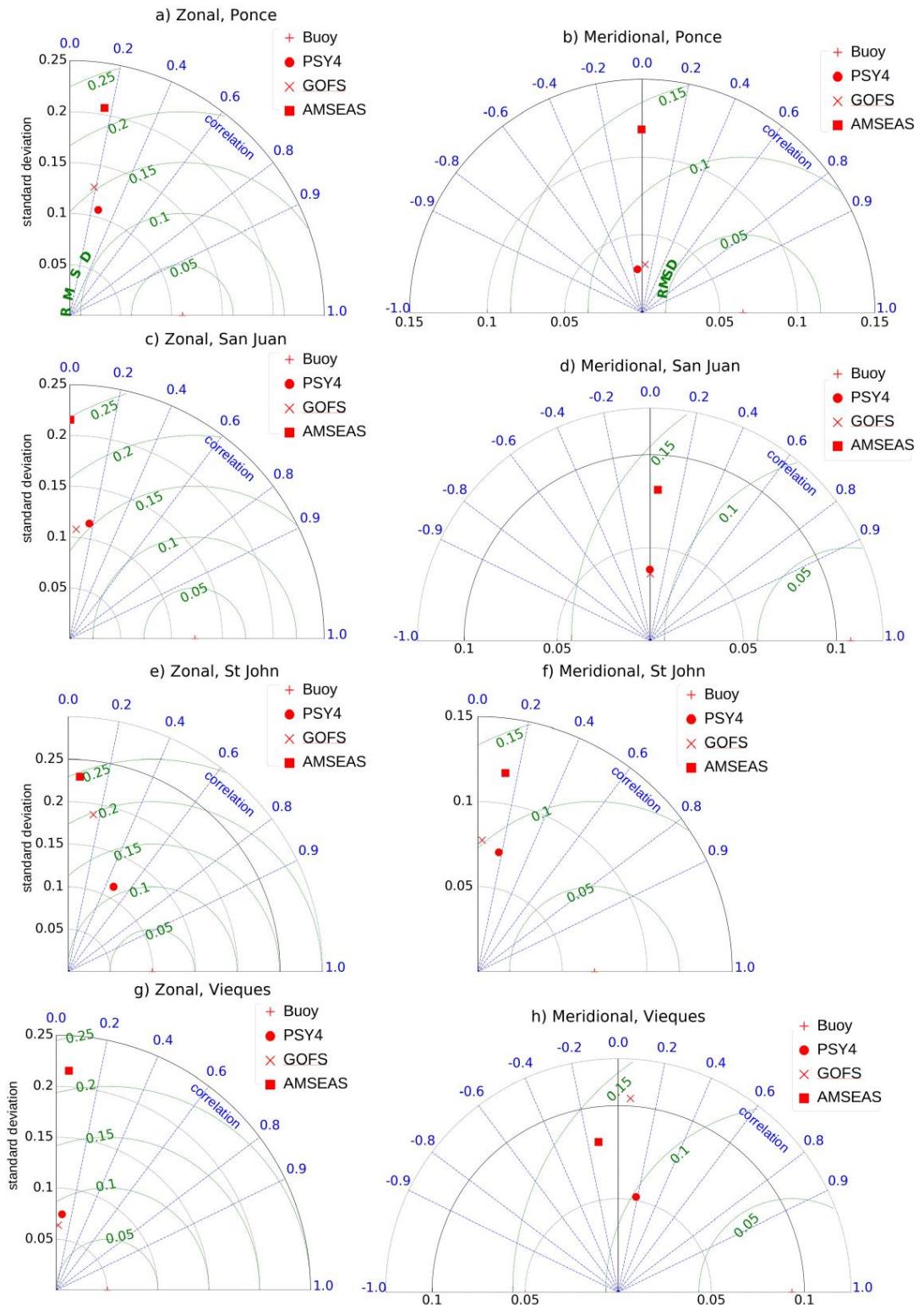


Figure 12: Taylor diagram for the nearshore velocity time series from the in-situ buoy measurements and the PSY4, GOFS and AMSEAS outputs. The left column shows Taylor diagrams for the zonal current velocities, and the right column the meridional current velocities. The rows from top to bottom show the plots for Ponce, San Juan, St John and Vieques respectively.

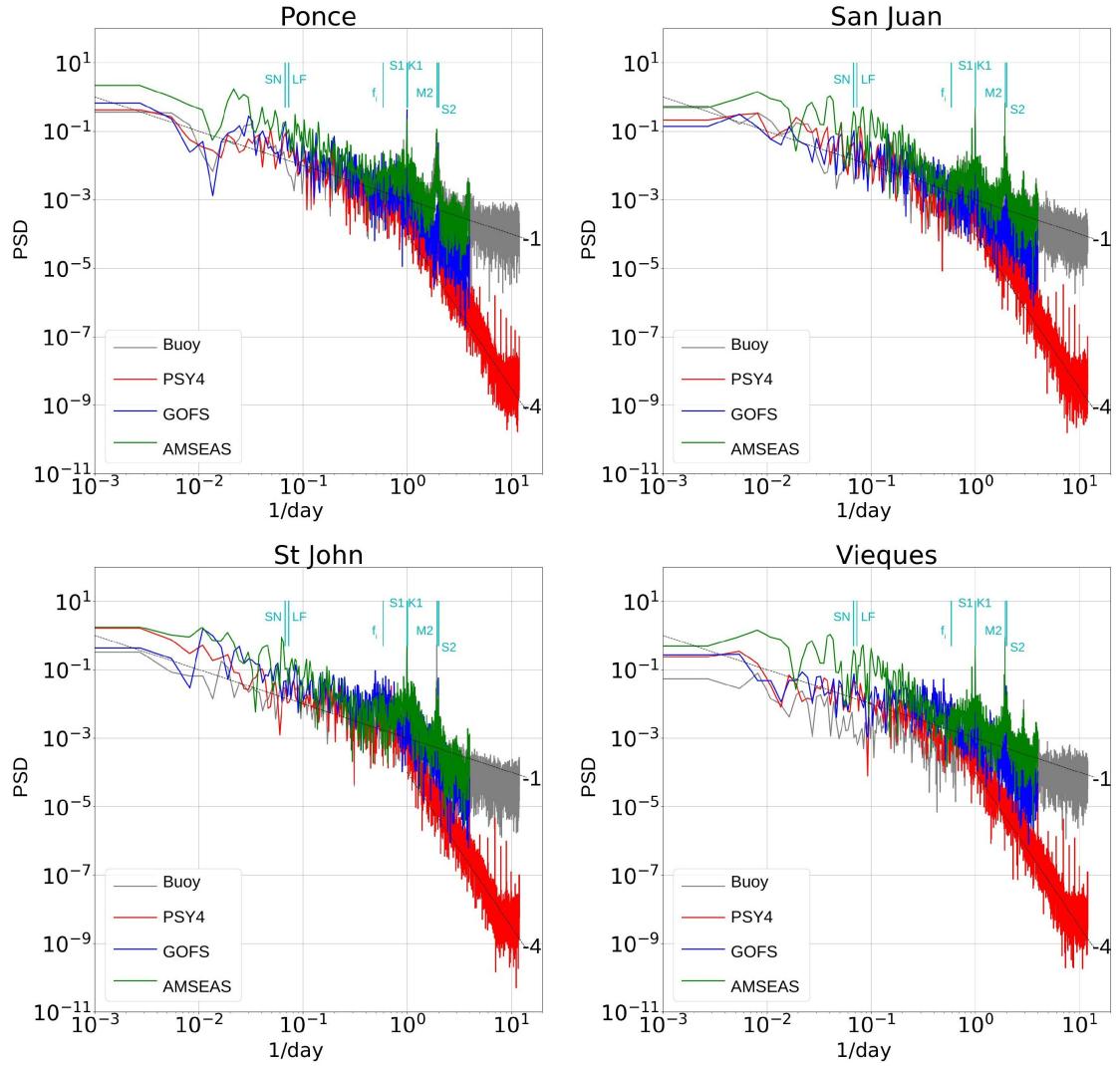


Figure 13: Temporal power spectral density (PSD) of the variance of the surface current velocity measured at the CariCOOS buoys at Ponce, San Juan, St John and Vieques along with model outputs at the same locations for a 1-year long data in 2016. The tidal frequencies for SN (spring-neap), LF (lunar fortnightly), S1, K1, M2 and S2 are marked in cyan. The dashed black lines indicate the slope of the PSD plots.

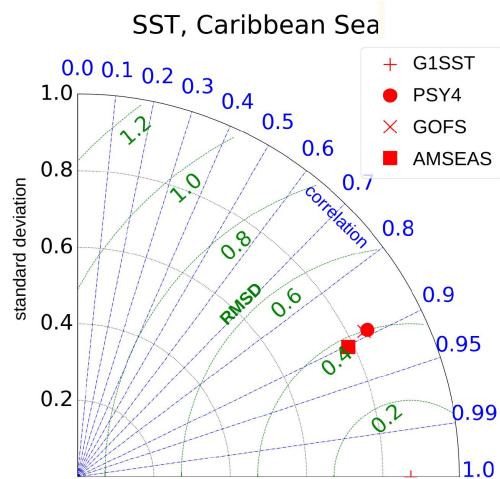


Figure 14: Taylor diagram showing the cross-correlation, standard deviation and *RMSD* of the SST from PSY4, GOFS and AMSEAS model outputs with respect to the G1SST data in 2016. The geographic range chosen for this analysis is denoted by the black rectangle in figure 3.

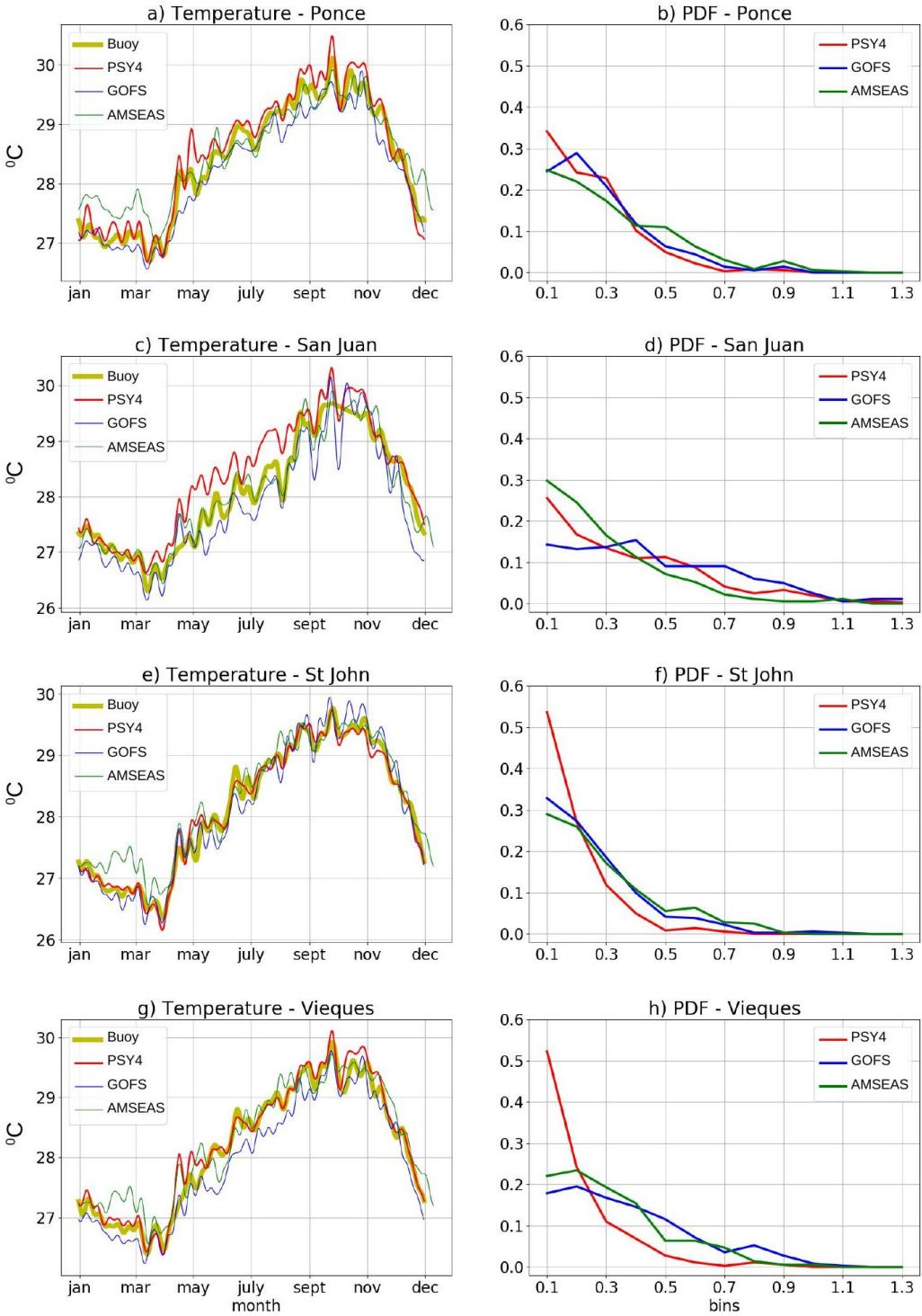


Figure 15: Seasonal variability of the sea surface temperature ^0C measured at the CariCOOS buoys at Ponce, San Juan, St John and Vieques, with model outputs at the same locations. The left column shows the time-series of the temperature, low-passed with a cutoff filter of 1 day. The right column shows the corresponding probability density functions (PDF) computed from the model errors. The x-axis in the PDF plot denotes the maximum error value of each bin, with a bin size of 0.1 units. The y-axis denotes the fraction of the number of points lying in a bin, divided by the total number of points in the time series. Refer to section 5.3 for details on the PDF calculation.

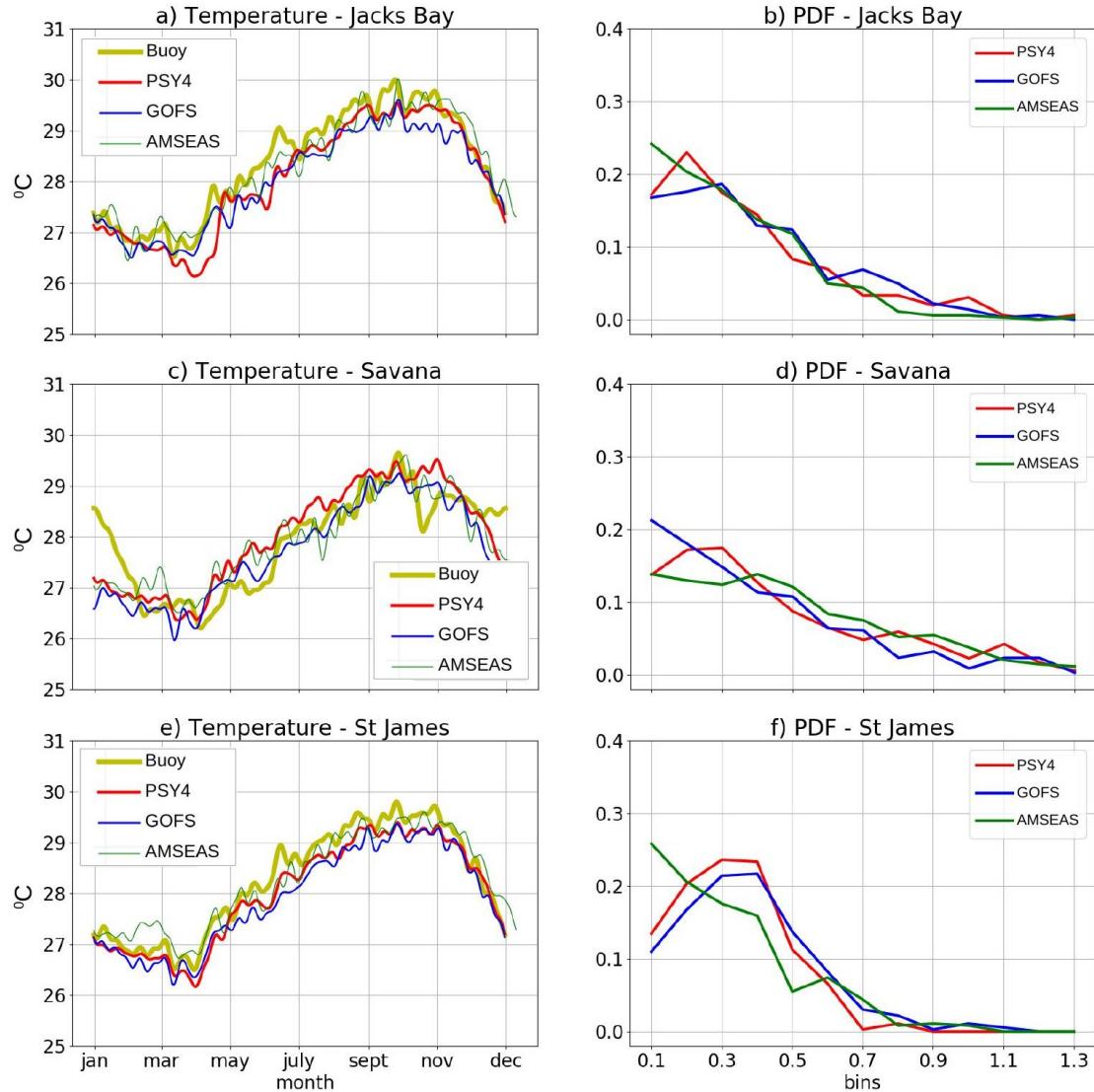


Figure 16: Seasonal variability of the benthic temperature (left panel) measured by HOBO loggers at the coral reef sites at Jacks Bay (13 m depth), Savana (16 m depth) and St James (27 m depth) in 2016, and the model outputs at the same locations. The right panel shows the PDF of the corresponding model errors. Refer to section 5.3 for details on the PDF calculation.