

1 **Statistical Downscaling of Seasonal Forecast of Sea**  
2 **Level Anomalies for US Coasts**

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6 **Key Points:**

- 7 • Sea level prediction from relatively coarse operational forecasts can be enhanced  
8 to finer coastal scales using statistical downscaling  
9 • Downscaling can be determined by multivariate linear regression trained from high-  
10 resolution reanalysis and its coarse-grained counterpart  
11 • This downscaling method significantly improves skill compared to bilinearly in-  
12 terpolated hindcasts at several US tide gauge locations

## Abstract

Increasing coastal inundation risk in a warming climate will require accurate and reliable seasonal forecasts of sea level anomalies at fine spatial scale. In this study, we explore statistical downscaling of monthly hindcasts from six current seasonal prediction systems to provide high resolution prediction of sea level anomalies along the North American coast, including at several tide gauge stations. This involves applying a seasonally-invariant downscaling operator, constructed by linearly regressing high-resolution ( $1/12^\circ$ ) ocean reanalysis data against its coarse-grained ( $1^\circ$ ) counterpart, to each hindcast ensemble member for the period 1982-2011. The resulting high resolution coastal hindcasts are significantly more skillful than the original hindcasts interpolated onto the high resolution grid. Most of this improvement occurs during summer and fall, without impacting the seasonality of skill noted in previous studies. Analysis of the downscaling operator reveals that it boosts skill by amplifying the most predictable pattern while damping the less predictable pattern.

## Plain Language Summary

The typical resolution of current seasonal climate forecast systems is too coarse to meet the needs for coastal ocean management and services including sea level forecast along U.S. coasts. This is becoming an increasingly important need as sea levels rise in a warming climate. To provide such information, we developed an efficient way to make predictions of sea level on much smaller spatial scales, on the order of 10 km. We tested our approach by using past forecasts (“hindcasts”) from existing climate forecast systems using the observed statistical relationship between sea level variations on scales of 100-1000 km and finer-scale coastal ocean observations. Our statistical approach improves the hindcast skill by which it projects and amplifies some of the predictable large basin-scale signals to coastal ocean fine structures.

## 1 Introduction

Sea level rise has increased the frequency, severity, and duration of coastal flooding in the past few decades (Sweet et al., 2014; Wdowinski et al., 2016; Ezer & Atkinson, 2014; Moftakhari et al., 2015). These changes can impact coastal communities through groundwater inundation (Rotzoll & Fletcher, 2013), beach erosion (Anderson et al., 2015) and storm-drain backflow and damage to the infrastructure (Habel et al., 2020). Coastal flooding frequency, due both to accelerated sea level rise (Sallenger et al., 2012; Nerem et al., 2018) and increasing sea level variability under climate change (Widlansky et al., 2020), is projected to steadily increase (Dahl et al., 2017; Krueel, 2016; Kriebel et al., 2015; Thompson et al., 2021; Wdowinski et al., 2016) and double by 2050 (Vitousek et al., 2017). This increasing risk to coastal infrastructure necessitates more accurate and reliable prediction of high-water level events months and seasons in advance.

Previous studies have demonstrated that dynamical seasonal forecasting systems can forecast sea level variation in the open ocean and at some coastal locations (Miles et al., 2014; McIntosh et al., 2015; Widlansky et al., 2017; Long et al., 2021), but in general prediction for coastal regions remains challenging. First, by definition the coasts are the numerical boundary of the ocean model and require special treatment in the numerical integration. Second, the spatial resolution of the current generation of forecast systems is too coarse to fully resolve the topography and fine-scale dynamics near the coasts. This issue could be addressed by employing much finer grid spacing in the global forecast models, but the resulting computational burden and model output storage requirements would be considerable, especially given the need for multiple ensemble members.

Alternatively, through the use of downscaling techniques (Pielke Sr & Wilby, 2012; Castro et al., 2005), regional forecast output with higher resolution than that of the orig-

62 inal coarse-grained forecast system can be obtained either dynamically, using regional  
 63 numerical models with higher resolution but in a limited domain, or statistically, by find-  
 64 ing a statistical relationship between coarse-grained and fine-scale data. Dynamical down-  
 65 scaling can potentially benefit from the resolved dynamics (other than parameterized pro-  
 66 cesses) and topography in the regional model compared to coupled GCMs (M. A. Alexan-  
 67 der et al., 2020; Shin & Alexander, 2020). Yet, it still requires substantial computational  
 68 and storage resources. Statistical downscaling, on the other hand, usually provide com-  
 69 parable results without the need for lengthy numerical integration and is often used as  
 70 a benchmark against which dynamic downscaling is evaluated (Goubanova et al., 2011).

71 This study aims to develop a high resolution forecast of coastal sea level anom-  
 72 lies from the existing seasonal forecast product using a simple regression-based statis-  
 73 tical downscaling method, whose results can serve as a benchmark for evaluation of fu-  
 74 ture development of more advanced statistical and dynamical downscaling methods. This  
 75 paper is organized as follows. Section 2 introduces the observational and reanalysis data  
 76 and model hindcast dataset used in this study. Section 3 describes the details of the regression-  
 77 based downscaling procedure. The validation of the downscaling technique and the skill  
 78 of the downscaled hindcasts are presented in Section 4. Section 5 includes the conclu-  
 79 sion.

## 80 2 Data description

81 To assess the skill of the statistical downscaling, we use monthly observations of  
 82 sea level from coastal tide gauges, sea surface height (SSH) fields from reanalysis and cou-  
 83 pled climate model hindcast products.

### 84 2.1 Tide Gauge Observation

85 Six tide gauge stations (black dots in Fig. 1: San Diego, San Francisco, South Beach,  
 86 Virginia Key, Charleston and Atlantic City) are chosen to represent typical coastal lo-  
 87 cations in the United States. Tide gauge observations usually have long time coverage  
 88 and are fairly consistent with other observations such as Satellite Altimetry (Long et al.,  
 89 2021).

### 90 2.2 GLORYS Reanalysis

91 GLORYS Ocean Reanalysis Version 12v1 (hereafter GLORYS; Jean-Michel et al.,  
 92 2021, and references therein) is a global eddy-resolving ocean and sea ice reanalysis, car-  
 93 ried out by the Copernicus Marine Environment Monitoring Service (CMEMS), which  
 94 provides monthly ocean fields in  $1/12^\circ$  horizontal resolution and 50 vertical levels, and  
 95 covers the period from 1993 to present. The reanalysis system assimilates along-track  
 96 satellite derived sea level anomalies, satellite derived sea surface temperature, and in situ  
 97 temperature and salinity vertical profiles, but not tide gauge data. However, extensive  
 98 comparison shows that the SSH output from GLORYS is highly correlated with tide gauge  
 99 observation along the U.S. coastlines (Amaya et al., 2022, and Fig. S1).

### 100 2.3 Hindcasts

101 We downscaled hindcasts from six current generation seasonal forecast systems (Ta-  
 102 ble S1), developed by different operational centers around the world, using models with  
 103 different resolution, assimilation and parameterization schemes (Merryfield et al., 2013;  
 104 Kirtman et al., 2014; Saha et al., 2014; Zhang et al., 2007). Hindcast ensembles of SSH  
 105 from each of these models, initialized at each calendar month from 1982 to 2011 with  
 106 lead time up to 12 months, were used in this study. We defined the lead-1 month as the  
 107 same month during which the model forecast is initialized. For example, if the forecast

was initialized on January 1st, then the monthly averaged forecast for January was the lead-1 month forecast (other studies might call it lead-0 or lead-0.5 month), February is the lead-2 month forecast, and so on. To remove the mean bias (model drift) in the hindcasts, we removed the initial time and lead-time dependent climatology determined separately for each model, which is a common practice for seasonal forecasts that are initialized with full field variables (Smith et al., 2013; Vannitsem et al., 2018).

### 3 Statistical Downscaling

We explore determining the downscaling relationship by relating an observational fine-scale dataset to a coarse-grained version of itself. The resulting relationship, when applied to the bias-corrected hindcasts, then yields downscaled hindcasts. In such practices, it is common that the predictor domain is different from the predictand domain (Goubanova et al., 2011), and the former is usually larger than the latter to capture the large scale variations. We set the predictor as the coarse-grained SSH anomalies determined by regridding the GLORYS reanalysis onto the climate model hindcast resolution ( $1^\circ \times 1^\circ$ ) using an areal conservative method, so that the downscaling operator derived from the observational datasets can be directly used to downscale the coupled model hindcasts. The predictand is set as the SSH anomalies from the GLORYS reanalysis on its original grid. Here, the anomalies were defined as departures from the monthly climatology for the years 1993-2018.

#### 3.1 Domain for Predictor and Predictand

To identify a relevant geographic domain for the predictor, the coarse-grained SSH anomalies were regressed onto each of the tide gauge observed sea level anomalies (Fig. 1). For the West Coast (Fig. 1a, b and c), coastal sea level variability is tightly confined to a narrow region along the coastline, dominated by coastally-trapped Kelvin Waves (Allen, 1975) whose source can be traced back to the Tropics (Meyers et al., 1998). The sea level variability at San Diego (Fig. 1a) is associated more strongly with coastal SSH signals and less with the open basin SSH pattern, as opposed to farther up the coast in South Beach (Fig. 1c) where the situation is reversed. Hence, to capture the large-scale pattern associated with coastal variability for all three representative tide gauges, the predictor domain for the West Coast was chosen to be all ocean points between 20N to 70N and 150W to 110W.

The dynamics of coastal variability for the East Coast are different from those of the West Coast. Along the southeast US coast (Fig. 1d and e), sea level variability is associated with the western boundary current (i.e., the Gulf Stream) and its extension. The weakly positive regression along the Gulf of Mexico indicates that part of the signal is from coastally-trapped waves propagating from the southeast US coast to the Gulf of Mexico (Pasquet et al., 2013; Ezer, 2016). In contrast, sea level variability near the northeast coast (Fig. 1f) appears mostly influenced by local processes. The predictor domain for the East Coast was therefore bounded between 20N to 50N and 90W to 60W.

The West Coast predictand domain was set to be the area within 200km of the coastline and within the larger predictor domain, while for the East Coast we adopt the Southeast and Northeast US Continental Shelf Large Marine Ecosystem regions (L. M. Alexander, 1993). We have tested different reasonable choices for the predictor and predictand domains, and our results are not sensitive to these choices.

#### 3.2 Downscaling procedure

The key element of statistical downscaling is to find a statistical relationship between the predictors and the predictands of interest (e.g. Goubanova et al., 2011, and many references therein). A multiple linear regression (MLR) in EOF space was used

to determined the statistical relationship between the coarse-grained and fine-scale SSH anomalies. The SSH anomalies were further truncated via EOF analysis to minimize the sampling uncertainty and thus reduce the effective degree of freedom (i.e. dimensionality) of limited observation records. Here we used predictor/predictand truncation of 34/10 EOFs for the West Coast, and 40/5 EOFs for the East Coast, respectively. Those truncation was chosen via extensive 10-fold cross-validation, where 90% of the data was used to determine the operator, which was then used to downscale the remaining 10%; this process was cycled through ten times, for each possible permutation of predictor/predictand truncation pairs (see details in Supplementary Text S1 and Fig. S2).

Then, the downscaling procedure via MLR becomes:

$$\mathbf{y} = \mathbf{B}\mathbf{x} + \epsilon \quad (1)$$

where  $\mathbf{x}$  and  $\mathbf{y}$  are vectors representing the principal component (PC) time series of predictor and predictand, respectively,  $\mathbf{B}$  is the multivariate regression coefficient (i.e. downscaling operator) matrix and  $\epsilon$  is the regression error. In order to account for spatial heterogeneity, the MLR is performed between two spatially varying fields, so that  $\mathbf{B}$  has nonzero off-diagonal elements. Moreover, EOF truncations for the predictor and predictand are different, so  $\mathbf{B}$  need not be square. Once the regression coefficient matrix  $\mathbf{B}$  is determined by minimizing the cross-validated regression error, we use it to downscale the hindcast in geographical space ( $\mathbf{Y}_m$ ):

$$\mathbf{Y}_m = \Phi\mathbf{B}\Psi^T\mathbf{X}_m$$

where  $\Phi$  and  $\Psi$  are the empirical orthogonal functions corresponding to the PC time series in  $\mathbf{y}$  and  $\mathbf{x}$  respectively.

### 3.3 Testing downscaling against interpolation

The statistical downscaling approach infers the forecast on a fine-scale grid from the forecast on a coarse grid by relating observed large-scale variations to fine-scale variations. We hypothesize that this approach is superior to instead filling in the fine grid using an interpolation technique, which uses information from the nearby grid points alone, but not from the large-scale patterns. In order to justify the statistical downscaling, we compared our downscaled hindcasts with a simple extrapolation/interpolation method to delineate local (interpolation via nearby coastal points) versus remote (basin to coastal scale) influences. To this end, we created an interpolated hindcast dataset: we fill the grid points on continents (i.e. extrapolation) by solving a Poisson's equation on a coarse  $1^\circ \times 1^\circ$  grid, and then use bilinear interpolation to find the values on the GLORYS ocean grid.

## 4 Results

### 4.1 Regression Validation

We first show how well the downscaling operators can reproduce the observed finescale coastal SSH anomalies. Figure 2 shows that the downscaled SSH anomalies are generally highly accurate within the West Coast domain (Fig. 2a), with the correlation between the downscaled SSH anomalies and the original GLORYS data above 0.9 for most locations. These correlations are reduced away from the coast, especially around 40N, regions with strong mesoscale eddy activity (Stammer, 1997) where our multivariate linear regression technique might have difficulty capturing the relationship between coarse-grained and fine-scale variability. Downscaled SSH anomalies are also highly correlated with GLORYS in the East Coast domain (Fig. 2b). However, the correlation is higher

199 along the Southeast than the Northeast continental shelf, suggesting that the sea level  
 200 variability in the former is associated with large scale SSH variations while the latter is  
 201 more influenced by local processes, which is also consistent with the regression maps in  
 202 Fig. 1. Overall, the linear regression captured the relationship between the coarse-grained  
 203 and fine-scale SSH anomalies with reasonable accuracy for both coastal regions, despite  
 204 their differing dynamics.

## 205 4.2 Forecast Skill

206 The patterns of skill of both downscaled and interpolated multi-model ensemble  
 207 mean hindcasts are generally similar (Fig. 3a and b). For the West Coast, the highest  
 208 skill is realized along the southwest coast, which could be attributed to coastally-trapped  
 209 Kelvin Waves. Low skill is found in the offshore region around 40N and in the Gulf of  
 210 Alaska. Downscaling generally improved upon interpolated forecast skill, significantly  
 211 so along the midlatitude coasts and in the Gulf of Alaska region (Fig. 3c). The SVD anal-  
 212 ysis of the downscaling operator (Fig. S6) shows that this improvement is primarily due  
 213 to one single-signed coarse-grained pattern along the coast that is amplified by the down-  
 214 scaling. For the East Coast, where overall skill is notably lower than for the West Coast,  
 215 downscaling still improved skill in a few areas, notably along the Northeast continental  
 216 shelf and in a Southeast continental shelf region away from the coastline. Again, much  
 217 of this improvement is dominated by one single-signed coastal pattern (Fig. S7). The  
 218 effectiveness of the statistical downscaling method varies across the models (Fig. S7 to  
 219 S12), with much more downscaling improvement for the CanCM3 and CanCM4 than the  
 220 other models.

221 Figure 4 shows the skill of hindcasts verified against tide gauge observations. Since  
 222 tide gauge data are not assimilated into GLORYS, they provide an independent verifi-  
 223 cation of our technique. For San Diego and San Francisco, statistically downscaled hind-  
 224 casts had significantly improved skill compared to interpolated hindcasts for almost all  
 225 lead times. There is no significant difference in the skill between downscaling and inter-  
 226 polation for South Beach except at lead-1 month. For the three stations on the East Coast  
 227 (Fig. 4d, e and f), downscaled forecasts are significantly more skillful than interpolated  
 228 forecasts for most lead times.

229 SSH forecast skill has strong seasonality (Long et al., 2021) that is typically a func-  
 230 tion of the verification month (Shin & Newman, 2021). Figure 5 show the skill for each  
 231 target month and lead time for San Diego and Charleston (other stations are shown in  
 232 Fig. S4). San Diego has higher skill for hindcasts verifying during the cold season than  
 233 for those verifying during the warm season, particularly for October through February,  
 234 consistent with a predictable signal due to ENSO-forced coastally-trapped Kelvin Waves  
 235 (Amaya et al., 2022). West coast sea level variability is also smaller in warm than in cold  
 236 months. The skill of interpolated forecasts has similar seasonality. However, the season-  
 237 ality of the skill is different than that of the skill difference. For example, statistical down-  
 238 scaling improves San Diego hindcast skill during both October-December and April-June.  
 239 San Francisco and South Beach show similar seasonality of skill and skill difference as  
 240 San Diego. In contrast, higher skill for the east coast stations is found for hindcasts ver-  
 241 ifying during late summer and early autumn, for both downscaling and interpolation,  
 242 which is also when the most significant downscaling skill improvement is found (Fig. 5  
 243 and S2). It is also interesting that the downscaling leads to minimal skill improvement,  
 244 or even a minor degradation of skill, during some winter months for most of the stations  
 245 examined here.

## 246 5 Conclusion

247 In this study, we demonstrated a statistical downscaling procedure for the seasonal  
 248 forecast of SSH anomalies for US coasts. The downscaling operator obtained by regress-

ing fine-scale SSH anomalies onto coarse-grained SSH anomalies can be applied to model forecasts to generate a high resolution product. We showed that our statistical downscaling technique can implicitly retrieve some of the skill existing in the fine-scale variation. This skill improvement would not have been obtained if we had only interpolated the model output to a fine-scale grid, because the fine-scale variability is not resolved in the coarse-grained model grid. Indeed, this downscaling technique significantly improved the hindcast skill of SSH anomalies for the US coasts compared to bilinearly interpolated hindcasts. When comparing the downscaled hindcast to the selected six tide gauge observations, we found that the downscaled hindcast improved skill for five stations at most lead times. While the downscaling did not alter the seasonality of the skill, the skill improvement has different seasonality, for reasons that remain to be explained. One possibility is that the downscaling was assumed to be independent of the seasonal cycle, so potential improvement might be expected if seasonal variation in the statistical relationship is included.

In this study, we have not aimed to “correct” the hindcasts for model error, apart from removing the mean bias. That is, when the reanalysis-derived downscaling operator is applied to the model hindcasts it is assumed that the model space is largely similar to that of the reanalysis. Of course, in reality these models generate different variability than observations or reanalysis, and their hindcasts may evolve in a different state space than nature (e.g., Ding et al., 2018), which may be why some model hindcasts are more improved than others by the downscaling. Applying a downscaling relationship determined entirely from observations to coarse-grained forecasts might therefore provide less high resolution skill than a downscaling trained on the forecasts themselves, which provides a focus for future work.

## Data Availability Statement

The data used in this study are available from the following sources: tide gauge observations (<https://psl.noaa.gov/data/tidal/>), GLORYS reanalysis (<https://datastore.cls.fr/catalogues/eu-copernicus-marine-service-global-reanalysis-glorys/>) and retrospective forecasts (<https://downloads.psl.noaa.gov/Projects/NMME/>).

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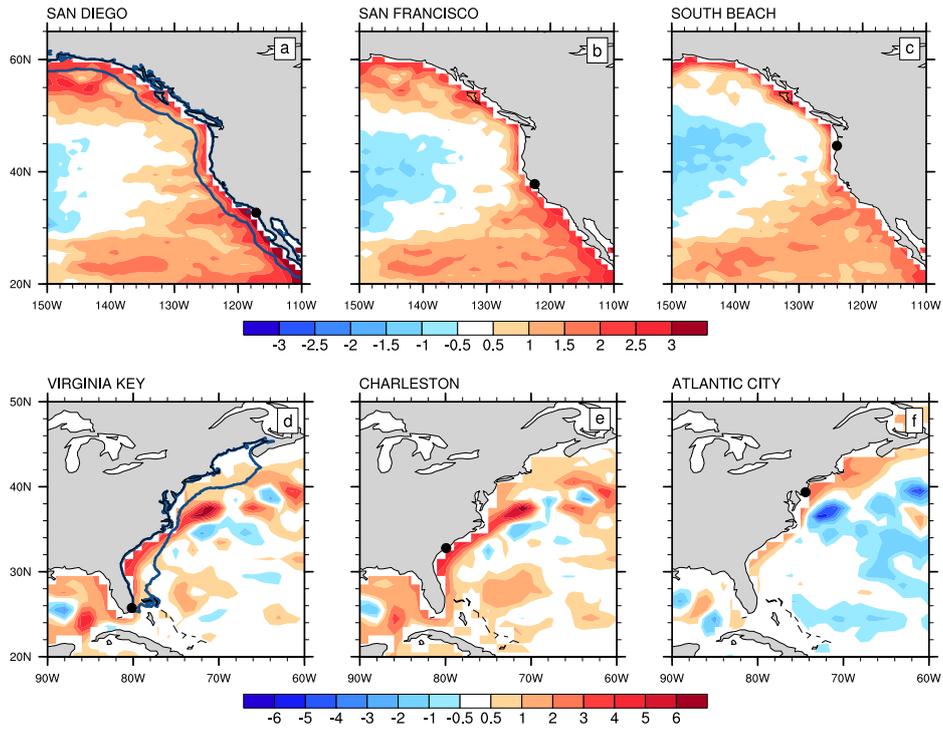
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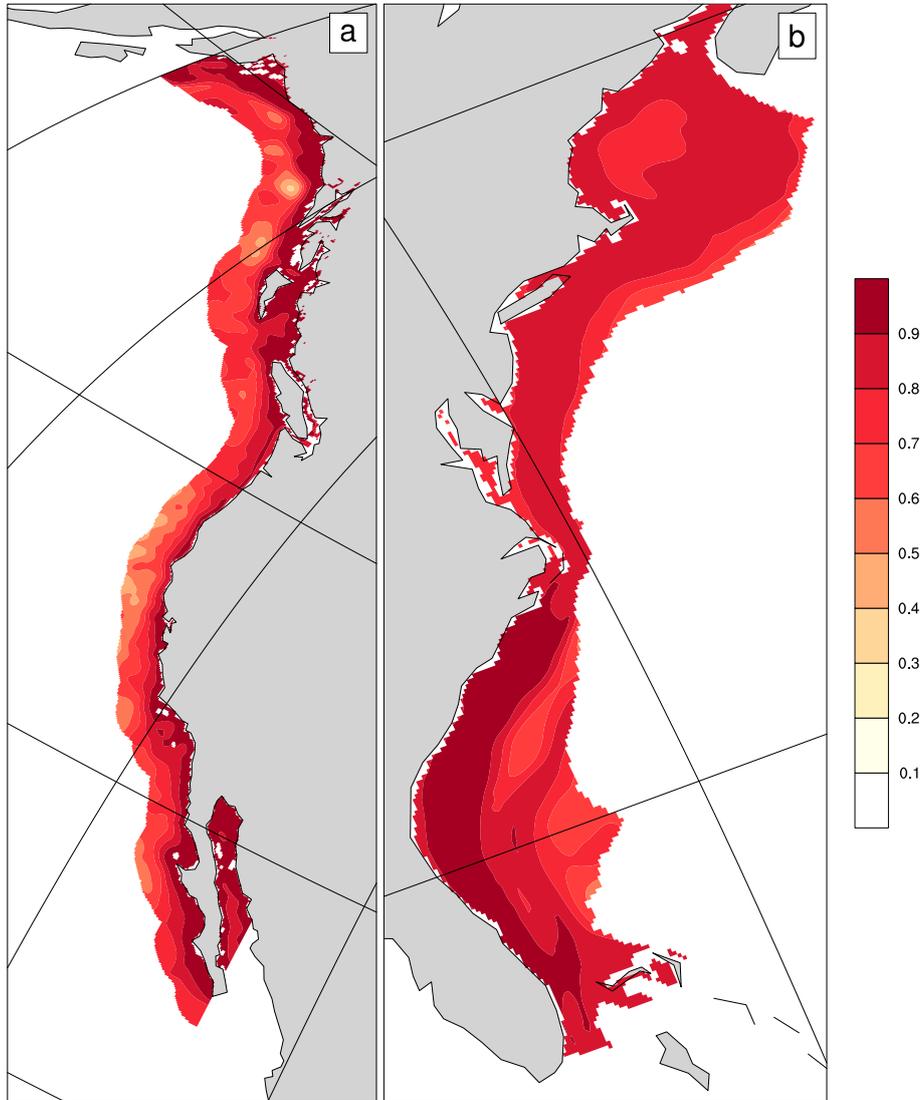
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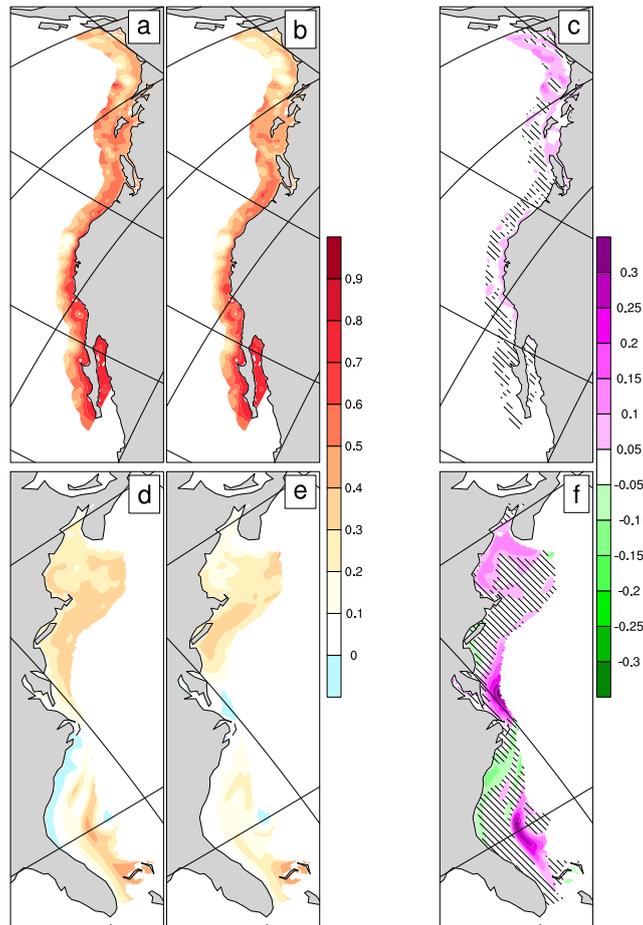
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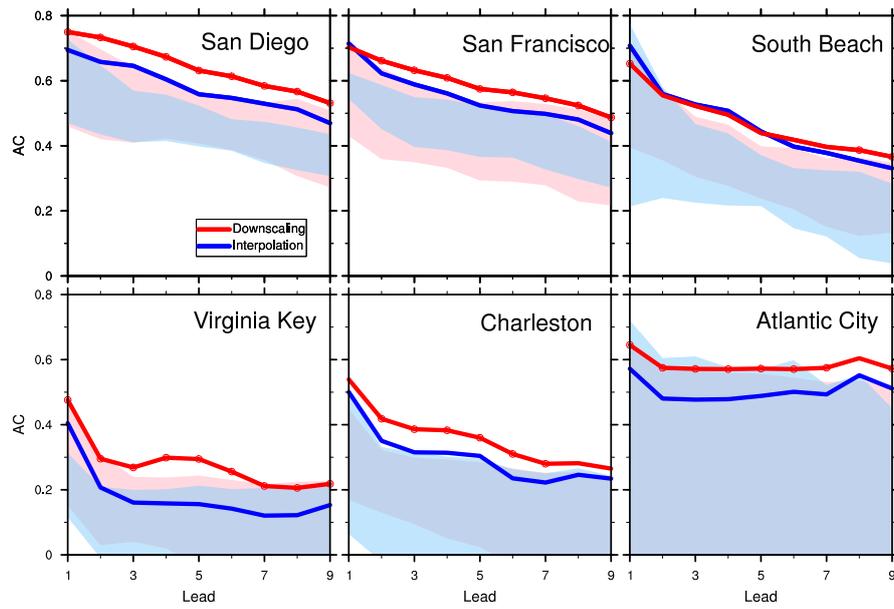
**Figure 1.** Regression maps of SSH anomalies from coarsened GLORYS reanalysis (1x1 grid spacing) onto each tide gauge observed sea level anomalies. The unit is centimeter. The name of each tide gauge is shown on the top of each panel. The black dots indicate the locations of the tide gauges. The blue line in panel (a) and (d) indicate the domain used in the MLR for predictand.



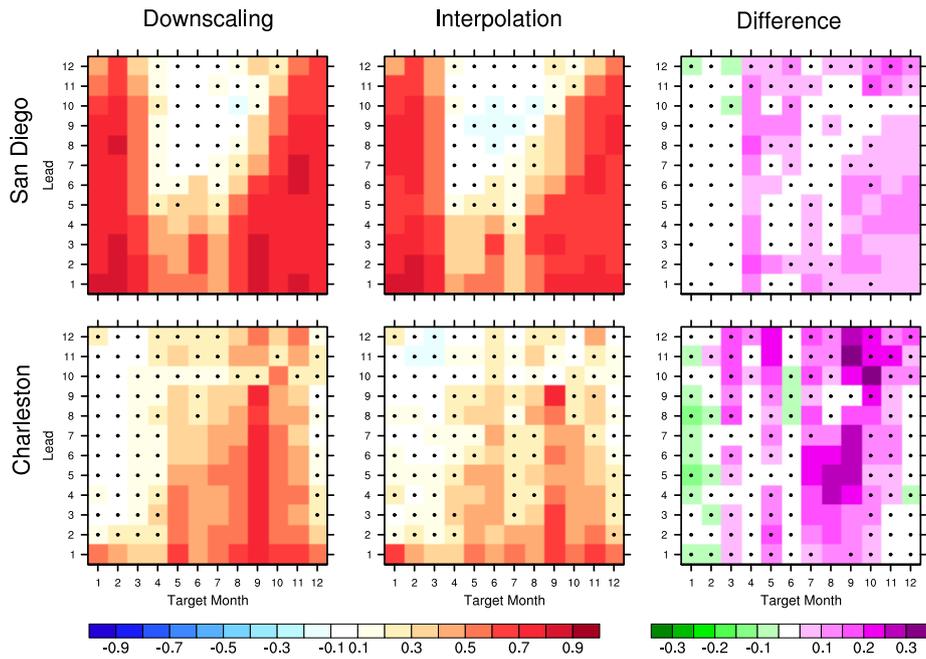
**Figure 2.** Temporal correlation coefficient between the SSH anomalies from GLORYS and the regression predicted SSH anomalies for (a) West Coast and (b) East Coast.



**Figure 3.** Anomaly correlation for Lead-7 month of (a,d) the downscaled hindcast and (b,e) the interpolated hindcast, verified against SSH anomaly from GLORYS reanalysis; (c,f) are the correlation difference between downscaling and interpolation; the hatching indicates the difference is not statistically significant at 0.1 level.



**Figure 4.** Anomaly correlation of the downscaled (red) and interpolated (blue) hindcast, verified against the tide gauge observation. The solid lines are the anomaly correlation of the respective ensemble mean of 6 models, and the shading indicates the skill range of all 6 models. The red circles indicate that the difference of the anomaly correlation between downscaling and interpolation is statistically significant at that lead time at 0.1 level.



**Figure 5.** The Anomaly Correlation of the ensemble mean of downscaling (left column) and interpolation (middle column) of the hindcast, verified against the tide gauge observation at San Diego and Charleston, for each lead time and target month; the right column shows the correlation difference of downscaling and interpolation of the hindcast (downscaling minus interpolation). The black dot indicates the correlation or correlation difference is not statistically significant at that lead time and target month at 0.1 level.