

Influence of Atmospheric Errors on Weeks 2–4 California Current System Predictions

M. GEHNE,^{a,b} J. DIAS,^b J. D. SCOTT,^{a,b} D. J. AMAYA,^b M. G. JACOX,^{b,c} M. A. ALEXANDER,^b AND A. A. CLUETT^c

^a *Cooperative Institute for Research in Environmental Sciences, University of Colorado Boulder, Boulder, Colorado*

^b *NOAA/Physical Sciences Laboratory, Boulder, Colorado*

^c *NOAA/Southwest Fisheries Science Center, Monterey, California*

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ABSTRACT: Understanding the forecast skill of ocean state anomalies on subseasonal time scales is critical for the effective use of ocean forecasts in marine resource management. Here, we evaluate error propagation in the European Centre for Medium-Range Weather Forecasts subseasonal to seasonal (S2S) coupled forecast system, specifically examining how atmospheric errors impact the accuracy of California Current System (CCS) ocean forecasts. Ensemble sensitivity analysis reveals regions where early lead-time atmospheric conditions can influence upper-ocean forecast errors, particularly in sea surface temperature and mixed layer depth. Conditioning on ensemble members with smaller atmospheric errors during the first 1–4 lead days yields a reduction in CCS errors for lead weeks 2–4 which is statistically significant for weeks 2–3. Improvements in the strength of both low and high pressure systems lead to better representation of near-surface alongshore winds, which constitutes improved atmospheric forcing of CCS ocean conditions. Here, we show how atmospheric weather patterns modulate the upper CCS by diagnosing the propagation of model errors in an operational S2S coupled forecast system. These results suggest that identifying more predictable atmospheric states early in the forecast can lead to more accurate CCS predictions for weeks 2–3.

SIGNIFICANCE STATEMENT: The oceanic region along the west coast of North America is a highly productive large marine ecosystem. Marine resource management balances human uses such as fishing, shipping, and tourism, with marine species and habitat conservation for future generations. Knowledge of the skill of forecasts of oceanic conditions in this region on time scales of several weeks is, therefore, of interest to marine resource management. In particular, advance knowledge of the timing of spring upwelling events and associated nutrient rich waters could provide information for fisheries on marine species distribution. Here, we show that forecasts associated with a better representation of weather patterns early in the forecast result in subsequent more accurate California Current System ocean state predictions. Our study suggests that improved weather forecasts over the northeast Pacific and western United States at earlier times are a promising pathway for more accurate oceanic weeks 2–4 predictions along the west coast of North America.

KEYWORDS: North Pacific Ocean; Atmosphere-ocean interaction; Forecast verification/skill; Coupled models; Model errors; Predictability

1. Introduction

The California Current System (CCS) is a highly productive large marine ecosystem in the northeast Pacific (Thompson et al. 2024). The CCS is situated along the western coast of North America and extends from about 47° to 22°N and covers the continental shelf region out to several 100 km offshore. The CCS is characterized by colder sea surface temperatures (SSTs) toward the north and warmer SSTs to the south, and the climatological 10-m winds travel from north to south along the coast (Figs. 1a–d), and so do the ocean currents in the CCS (Figs. 1e–h).

During boreal spring and summer, surface winds along the coast intensify (Figs. 1b,c), leading to enhanced offshore Ekman transport and associated shallower mixed layer depths (MLDs) (Fig. 1g).

Seasonal upwelling during the spring and summer brings nutrient-rich waters to the surface, influencing marine species distribution and abundance (Jacox et al. 2018). The seasonal cycle in upwelling is more pronounced in the northern part of the CCS (Huyer et al. 1979) and can be influenced by the timing and intensity of weather systems over the North Pacific. Changes in the timing of the upwelling, or interruption of the alongshore equatorward winds due to the passage of low pressure systems from the Gulf of Alaska, can have far-reaching impacts on nutrient availability, primary production, resource availability, and management for the year (Barth et al. 2007).

Ocean forecasts are increasingly desired for decision-support tools in management strategies from weeks to years (NOAA Fisheries 2021). Subseasonal to seasonal (S2S) forecasts are characterized by time scales of 2 weeks to less than a season (Vitart et al. 2017). Investigating the influence of oceanic and atmospheric processes on S2S predictability and forecast skill in the CCS is an area of active research. For example, oceanic

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Corresponding author: Maria Gehne, maria.gehne@colorado.edu

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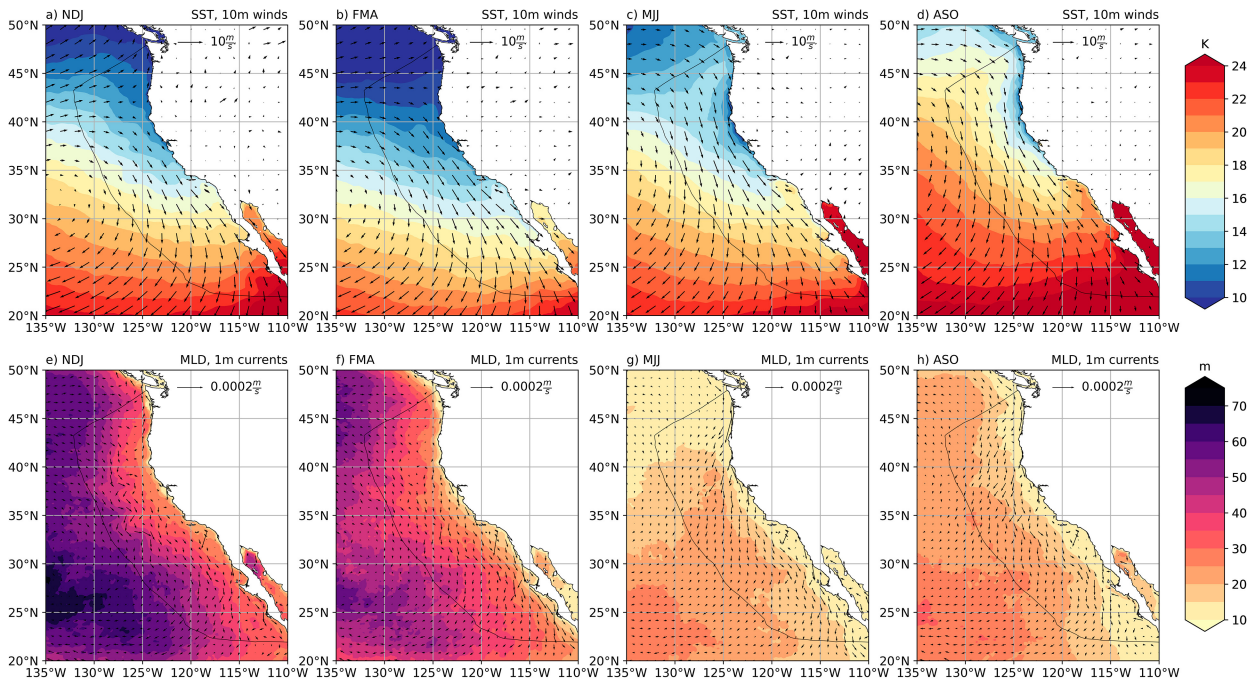


FIG. 1. Composites of GLORYS SST and 10-m winds for seasons (a) NDJ, (b) FMA, (c) MJJ, and (d) ASO and GLORYS MLD and ocean currents at 1-m depth for seasons (e) NDJ, (f) FMA, (g) MJJ, and (h) ASO. The CCS is outlined in black.

Kelvin waves from the tropical Pacific propagate northward along the North American coast influencing CCS SSTs, sea surface heights (SSHs), and bottom water temperatures (Amaya et al. 2022; Alexander et al. 2025). In addition, oceanic coastally trapped waves can also influence ocean currents (Gómez-Valdivia et al. 2017; Hughes et al. 2019). Additionally, both the Madden-Julian oscillation (MJO) and El Niño–Southern Oscillation (ENSO) have been shown to impact anomalous nontidal residual water levels along the west coast of North America on S2S time scales (Arcodia et al. 2024). Identifying sources of model skill in predicting CCS oceanic variables potentially enables better support for decision-makers (Cluett et al. 2024).

The atmosphere and ocean evolve on different time scales, with short-lived atmospheric forcing impacting ocean states at much longer times. In the northeast Pacific, large-scale atmospheric variability associated with the Aleutian low in winter and the North Pacific high in summer drives SST variability on monthly to decadal time scales (Cayan 1992; Favre and Gershunov 2006; Chhak et al. 2009). In return, low-frequency ocean variability can feed back on the atmosphere (Frankignoul and Hasselmann 1977; Sura et al. 2006), and coupled atmosphere–ocean modes of variability can extend the predictable component of a forecast. Coupled modes in the North Pacific are the North Pacific Gyre Oscillation (Di Lorenzo et al. 2008) and the Pacific meridional mode (Chiang and Vimont 2004; Amaya 2019), in addition to ENSO and the Pacific decadal oscillation (PDO; Mantua and Hare 2002). In the context of S2S prediction, these low-frequency modes take the role of boundary/initial condition forcing as their evolution exceeds the length of a forecast.

Errors in coupled forecast models grow rapidly (Beverley et al. 2023), with ocean errors lasting longer than the atmospheric model errors that generated them. Therefore, improving our understanding of how errors develop and propagate within an S2S forecast system helps us to both identify the underlying error sources and better interpret forecasts in real time. Here, we investigate to what extent atmospheric model errors within the first forecast week, and in particular during the first 4 days, affect ocean errors in CCS predictions at lead weeks 2–4. By combining established methods in a novel, integrated manner, this work aims to assess the influence of atmospheric conditions and errors on ocean states within a fully coupled ocean–atmosphere forecast system.

In the following, we introduce data, model forecasts, and methods in section 2; go through the conditional error and skill analysis in section 3; and discuss the results in section 4. Conclusions are presented in section 5.

2. Data and methods

a. Data

European Centre for Medium-Range Weather Forecasts (ECMWF) S2S coupled reforecasts (Vitart et al. 2017) from model year 2022 (model version CY47R3) are initialized twice per week from 2002 to 2021 with daily output for lead times of 46 days. The ensemble includes 11 ensemble members generated by using singular vectors and ensemble data assimilation perturbations that are added to the control analysis in the atmosphere, and ocean perturbations are generated during the ensemble data assimilation step as described in Zuo et al. (2017). For verification, the fifth generation ECMWF atmospheric

reanalysis (ERA5; [Hersbach et al. 2020](#)) is used for the atmosphere, and Global Ocean Reanalysis and Simulation (GLORYS) 12v1 product ([Lellouche et al. 2021](#)) and Ocean Reanalysis System 5 (ORAS5; [Zuo et al. 2019](#)) are used for the ocean variables. Verification fields are regridded conservatively to match the lower-resolution model output grid of 1.5°. Daily averages are used, which are computed from 3-hourly values for ERA5. Ocean reanalyses are expected to exhibit larger discrepancies than atmospheric reanalyses due to the limited availability of oceanic data. To confirm that the main results are not dependent on a single reanalysis product, we employed both, yielding qualitatively similar results. This increases the confidence in the results presented in this work. For brevity, we show only the results with respect to GLORYS throughout.

Native definitions of MLD differ between GLORYS, ORAS5, and S2S reforecasts. To make direct comparisons between the three, we use 3D temperature and salinity fields to recompute the MLD from GLORYS based on the definition used in ORAS5 and the ECMWF model reforecasts. Here, MLD is defined as the depth where ocean density increases by 0.01 kg m^{-3} relative to the near-surface value at 10 m. This definition can result in too shallow mixed layers during periods of strong solar heating ([de Boyer Montégut et al. 2004](#)), but consistency among the data sources is essential. We also examined SST and SSH from GLORYS and ORAS5 and ERA5 500-hPa geopotential height (Z500), 200-hPa winds (U200, V200), 10-m zonal and meridional winds (u10, v10), and 2-m temperature and friction velocity (u^*) derived from model output and ERA5.

b. Climatology

Forecast anomalies are computed based on a lead-dependent daily model climatology from 2002 to 2021. The lead-dependent daily model climatology is computed as follows: There are 104 dates in each year with forecast initializations. Forecasts for each available day of the year are averaged across all years and ensemble members to give the mean daily seasonal cycle at the 104 days of the year with initializations. The days in between the 104 initializations are linearly interpolated for each lead time. This gives mean daily seasonal cycles for each day of the year and lead time. These mean daily seasonal cycles are then smoothed by only keeping the mean and first three harmonics (assuming 366 days in the year) at each lead time and are used as the climatology. ERA5, ORAS5, and GLORYS anomalies are computed analogously using daily data (no interpolation necessary) and a climatology based on retaining the mean and first three harmonics of the daily average seasonal cycle from 2002 to 2021.

c. Methods

Skill on S2S time scales is commonly assessed by taking successively longer averages at longer lead times to balance signal and noise contributions. We follow [Zhu et al. \(2014\)](#) and define averaging windows by denoting lead time and averaging time by 1d1d, 2d2d, 4d4d, 1w1w, 2w2w, and 3w3w. Here, 1d1d is a 1-day average starting on day 1, 4d4d is a 4-day

average starting on day 4, 1w1w is a 1-week average starting at 1-week lead (corresponding to the week 2 average), and 2w2w is the week 3 and week 4 average. Because of the importance of coastal upwelling to the northeast Pacific marine ecosystem, we focused on the spring/summer upwelling season May–July (MJJ).

1) SKILL METRIC

The absolute error (AE) over a region is defined as the regional average of the absolute error at each grid point weighted by the cosine of latitude. For ocean states, persistence can be a good forecast of the state at short lead times. A damped persistence forecast is defined as the ocean state anomaly at initial time multiplied by its autocorrelation. The autocorrelation is computed as the correlation at each grid point between the ocean state at initial time and the ocean state at each lead time across all dates. The advantage of a damped persistence forecasts is that it takes the initial observed anomaly into account and damps toward climatology with lead time to combine the short-term skill of the observed anomaly with the long-term skill of climatology ([Niraula and Goessling 2021](#)).

2) ENSEMBLE SENSITIVITY ANALYSIS AND CONDITIONING

To identify where early lead-time atmospheric model errors are most likely to impact ocean state errors, we use ensemble sensitivity analysis (ESA; [Ancell and Hakim 2007](#); [Limpert and Houston 2018](#); [Duc et al. 2023](#)). Specifically, we compute the ensemble correlation (C) between a response function and atmospheric anomalies at earlier lead times. The response functions used here are AE in model ocean forecasts over the CCS. To take into account the difference in atmospheric and oceanic time scales, and to reduce the number of figure panels, we use weekly averaged forecasts here. Daily computations were performed as well with similar results. In particular, we use the following equation to compute C between AE and atmospheric anomalies X (e.g., Z500, v10) as

$C(d, w, l, \text{lat}, \text{lon})$

$$= \frac{\frac{1}{N} \sum_{n=1}^N [\text{AE}(d, w, n) - \overline{\text{AE}}^n][X(d, w - l, n, \text{lat}, \text{lon}) - \overline{X}^n]}{\text{stdev}^n(\text{AE})\text{stdev}^n(X)}, \quad (1)$$

where

$$\text{stdev}^n(\text{AE}) = \sqrt{\frac{1}{N} \sum_{n=1}^N [\text{AE}(d, w, n) - \overline{\text{AE}}^n]^2}, \quad (2)$$

$$\overline{\text{AE}}^n = \frac{1}{N} \sum_{n=1}^N \text{AE}(d, w, n), \quad (3)$$

and similarly for $\text{stdev}^n(X)$ and $\overline{X}^n$. Here, d is the initial date, w is the lead week, $l \in [0, w]$ is the lag week, lat and lon are the latitude and longitude, n is the ensemble member, and

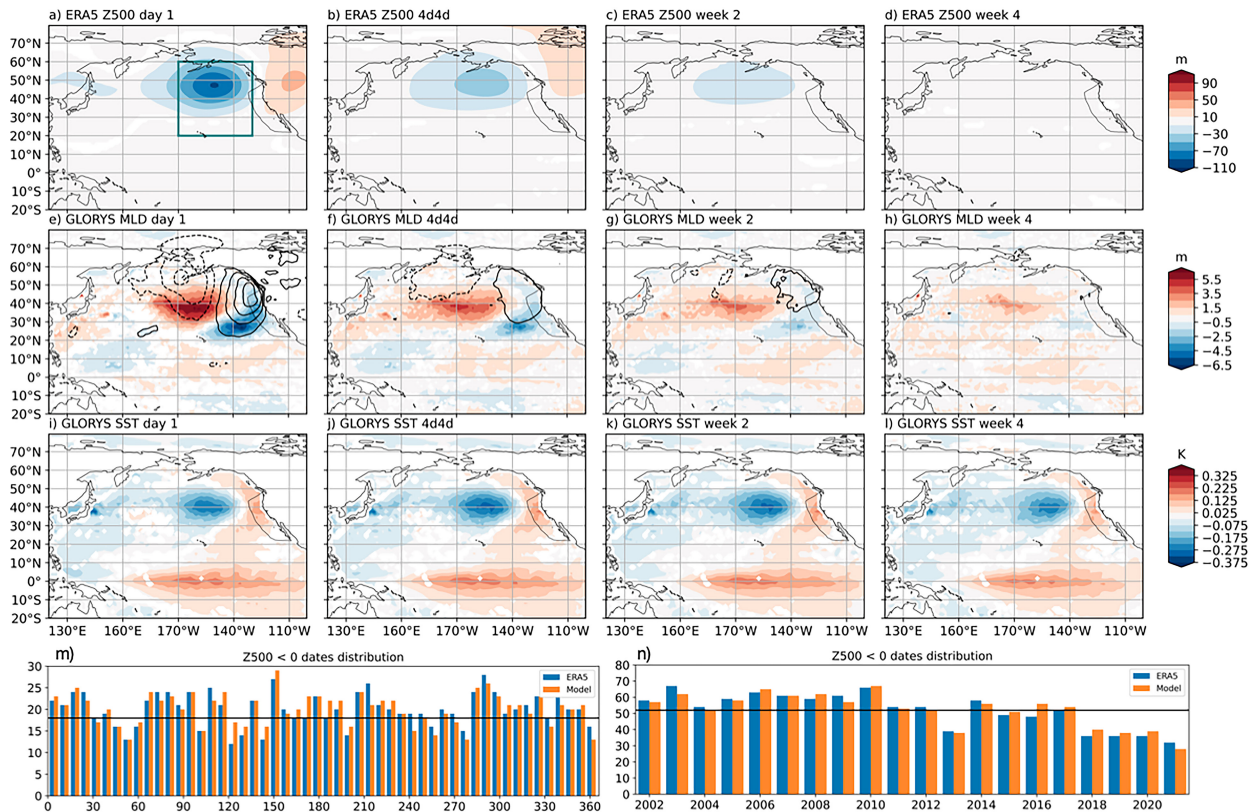


FIG. 2. Composites of Z500, v_{10} , MLD, and SST anomalies conditioned on negative Z500 anomalies at day 1 of the forecast in the region 20° – 60° N, 170° – 130° W [outlined in (a)]. Anomaly composites for ERA5 Z500 for (a) day 1, (b) days 4–7, (c) week 2, and (d) week 4 and black contours of anomaly composites of v_{10} at the same lead times with contours starting at 0.25 m s^{-1} and a contour interval of 0.5 m s^{-1} , and negative contours are dashed. Anomaly composites for GLORYS MLD for (e) day 1, (f) days 4–7, (g) week 2, and (h) week 4 and for GLORYS SST for (i) day 1, (j) days 4–7, (k) week 2, and (l) week 4. The outline of the CCS is drawn in black in each panel. Histograms of negative Z500 anomaly counts for model and ERA5 by day of year aggregated (m) per week and (n) by year.

N is the number of ensemble members. As the expectation is that the ocean forecasts respond to the atmospheric circulation, the ocean error lags the atmosphere from $l = 0$ weeks (atmosphere and ocean state are simultaneous weeks) to $l = w$ weeks (the atmosphere leads the ocean by w weeks).

Previous studies have pointed out the limitations of ESA, including the limitation of nonlinearity in the ensemble perturbation evolution. The presence of nonlinearities will lead to weak correlations in the analysis outlined above. There is evidence, however, that even in the presence of nonlinearities, ESA can be used effectively out to medium range (Chang et al. 2013; Ancell and Coleman 2022). Significant ESA correlations indicate regions where the forecast ocean state error AE in the CCS is sensitive to the atmospheric model state at earlier lead times. Previous studies have used ESA expressed as a regression coefficient or a standardized version of it with the same units as the response function. Here, we use the correlation coefficient for easier comparison of sensitive regions across response variables (SST, MLD, and SSH) with different units. See below for the estimation of statistical significance.

Conditioning on ensemble members with smaller errors in a certain region at a particular lead time is done similarly to

Dias et al. (2018). In particular, we choose the best three and poorest three ensemble members in terms of smallest and largest atmospheric AE at lead time 1d4d (days 1–4), respectively, in the regions identified using ESA, 20° – 60° N, 170° – 130° W for Z500 and 10° – 60° N, 150° – 120° W for v_{10} .

3) STATISTICAL SIGNIFICANCE TESTING

Statistical significance for composites is estimated by subsampling 90% of all composite dates 500 times and computing the mean over the subsamples. If the interval between the 5th and 95th percentile of the means does not overlap 0, the median pattern is deemed statistically significant.

For the ESA correlations, statistical significance is estimated by first computing the ESA correlation between a random normal distributed index instead of the AE and atmospheric anomaly fields. This estimates the correlation values expected from the fact that the atmospheric anomalies are spatially autocorrelated. From this random correlation, we select 90% of the dates randomly 500 times and compute the median for the sample. The median of the ESA correlations for a given season, lead time, and lag is deemed significantly different from zero if it is outside the 10th–90th percentile

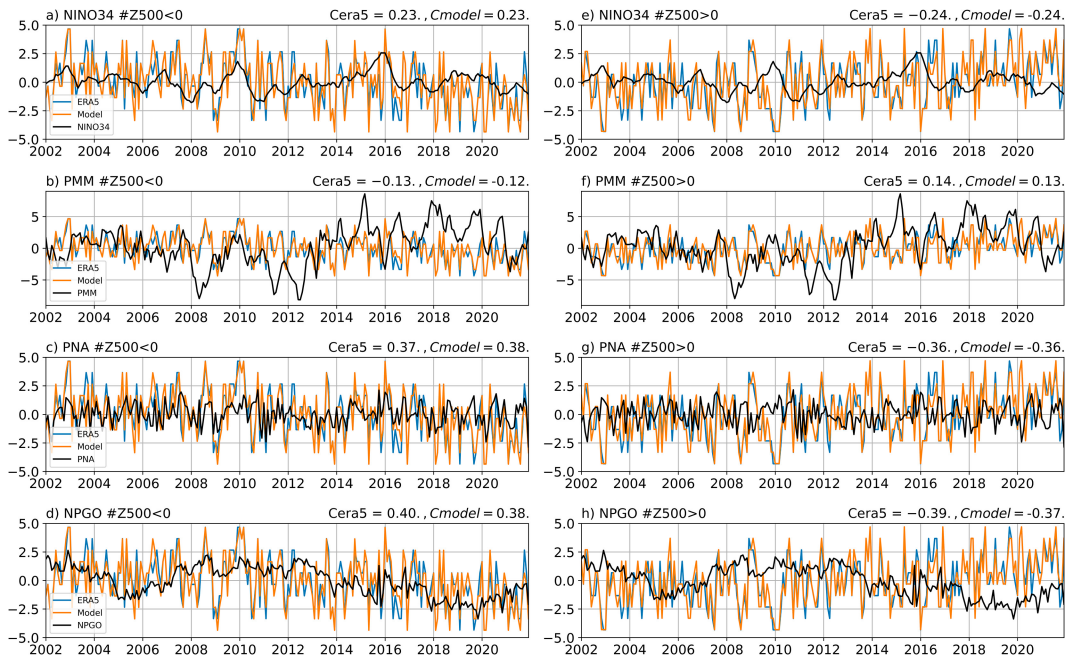


FIG. 3. Time series of monthly counts of positive and negative Z500 anomalies at day 1 of the forecast in the region 20° – 60° N, 190° – 230° E (orange) and ERA5 Z500 anomalies on the same dates (blue). Also shown are the monthly time series of Niño-3.4, PMM, PNA, and NPGO (black). The correlation coefficients between the counts and the time series for both ERA5 and model are shown in the right title and are significant at the 95% level based on a p -value test.

interval of the random ESA correlations for the same season, lead time, and lag.

Statistical significance of the differences between good and poor ensemble members is estimated similarly to the composites. But, instead, the condition is if the 10th and 90th percentiles of the means do not overlap 0, the median pattern is deemed statistically significant.

Estimates of statistical significance of the regression coefficients are based on removing 10% of the data 500 times and computing the regression coefficients, and locations where the 5th–95th percentile range of the difference does not include zero are deemed significant.

3. Conditional error analysis

Figure 2 illustrates the difference in time scales between atmosphere and ocean variability. Here, we conditioned on negative Z500 anomalies at day 1 of the forecast in the region 20° – 60° N, 170° – 130° W. The initial negative Z500 anomaly, and consistent v10, weakens in amplitude within the first week (Figs. 2a,b), while the SST anomaly remains similar at week 2 and beyond (Figs. 2i–l), emphasizing the much longer persistence in the ocean relative to the atmosphere. SST anomalies are actually stronger at days 4–7 than on day 1 (Figs. 2i,j), whereas MLD anomalies are strongest on day 1 and decay slower than the atmospheric but faster than the SST anomalies (Figs. 2e–h). Figure S1 in the online supplemental material shows the analogous composites on positive Z500 anomalies at day 1 with similar temporal variability.

The composite patterns in Fig. 2 have a strong resemblance to the positive phase of ENSO, with positive SST anomalies in the equatorial Pacific and along the western coast of North America. The MLD anomalies are positive in the central North Pacific, consistent with the negative SST anomalies. ENSO is known to affect the Aleutian low and thereby North Pacific SSTs. However, the initial dates that contribute to this composite are evenly distributed throughout the year, and the time series of monthly counts of negative Z500 initial dates does not show a dominant relationship to a coupled climate mode (Fig. 3).

a. Ensemble sensitivity analysis

The ESA correlation of AE_{SST} in the CCS and Z500 anomalies (Figs. 4a–f) shows regions of negative and positive correlations over the North Pacific and North America. Negative regions can be interpreted as locations where negative Z500 anomalies at earlier lead times lead to larger CCS AE_{SST} and positive correlation regions are where positive Z500 anomalies are related to larger CCS AE_{SST} . Statistical significance of the correlations is estimated by taking the distribution of correlations at each grid point and assessing where 95% of the distribution has the same sign as the median.

The ESA correlation of AE_{SST} in the CCS at lead weeks 2–4 to Z500 has the signature of an extratropical wave train over the North Pacific for lags up to 2 weeks with the strongest correlations occurring at lag 0 and 1 week (Fig. 4). Near the surface, the sensitivity to v10 is dynamically consistent

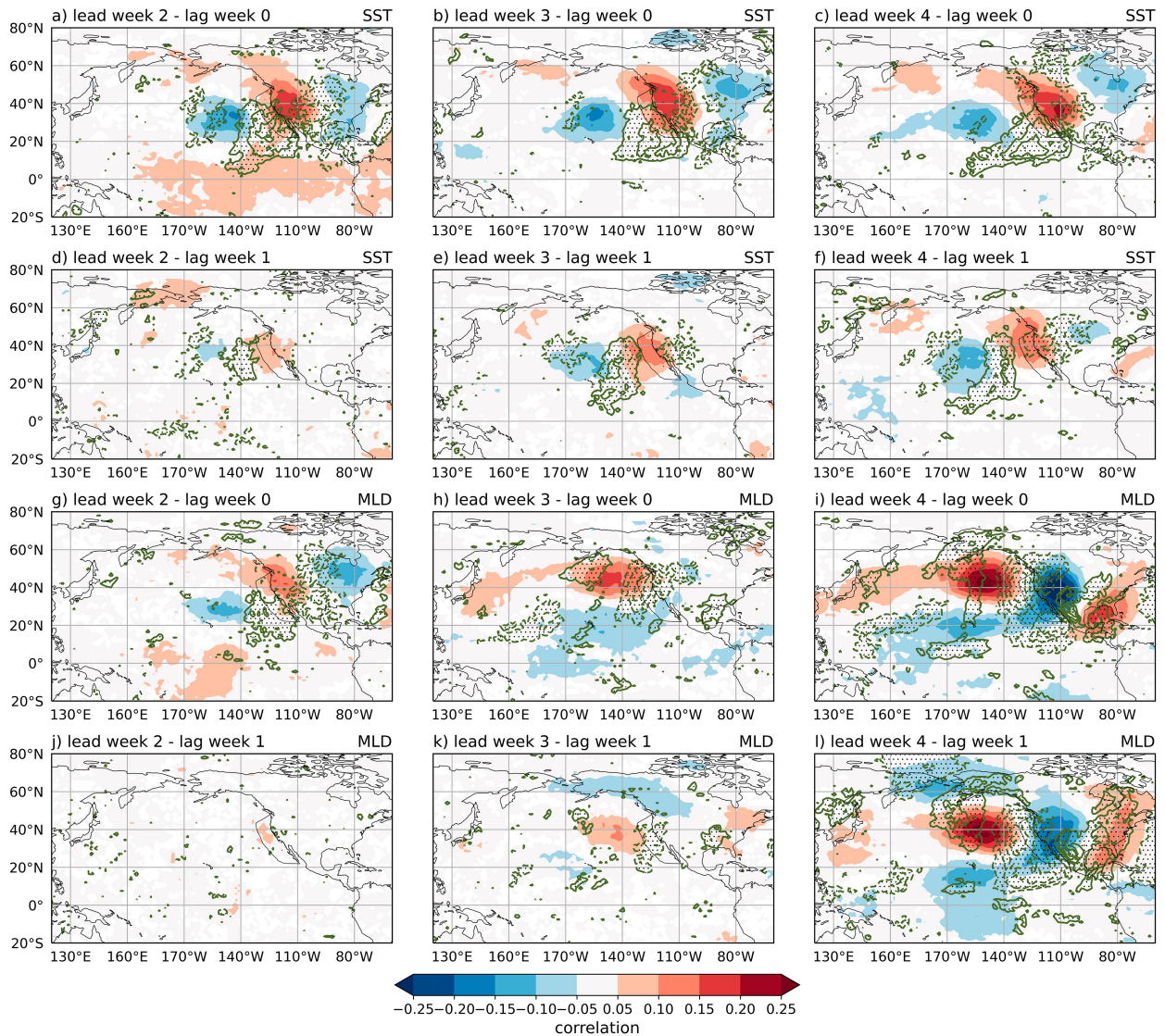


FIG. 4. Ensemble sensitivity correlation during MJJ for AE in the CCS to Z500 (shading) and v10 (contours) for SST at (a) lead week 2, lag week 0; (b) lead week 3, lag week 0; (c) lead week 4, lag week 0; (d) lead week 2, lag week 1; (e) lead week 3, lag week 1; and (f) lead week 4, lag week 1 and for MLD at (g) lead week 2, lag week 0; (h) lead week 3, lag week 0; (i) lead week 4, lag week 0; (j) lead week 2, lag week 1; (k) lead week 3, lag week 1; and (l) lead week 4, lag week 1. The outline of the CCS is drawn in black in each panel. Here, lead week is the lead time of the atmospheric forecast (Z500 and v10), and lag week is how many weeks the SST or MLD forecast lags the atmosphere. Contour lines start at 0.05 and increase by 0.1, and negative contours are dashed. Shading shows only correlation values that are significantly different from zero, and stippling indicates statistical significance for the contours. See [section 2c\(3\)](#) for details of the statistical significance computation.

with a low pressure system in the North Pacific at 160°W, 30°N moving north and eastward with decreasing lag. Other dynamical variables such as winds at 200 hPa, u10, and friction velocity show consistent signals with varying intensities (Fig. 5). When looking at winds, wave train signatures look different to the more commonly shown geopotential. For zonal wind, the geopotential centers of the wave train will be situated on the north-south nodes of the wind signals, since zonal winds will be strongest to the north and south of geopotential anomalies. The sensitivity regions for MLD (Figs. 4 and 5g-l) also show a

wave train signature over the North Pacific, although with a slightly different track.

Although the correlation values are small, they are statistically significant. The wave train pattern in Z500 together with consistent signals in upper-level and surface winds indicates a physical link between atmospheric flow and ocean state AE in the CCS. It is, therefore, a reasonable assumption that ensemble members with small errors in the atmospheric circulation would also have smaller errors in the CCS ocean state. To test this hypothesis, we perform a conditional skill analysis.

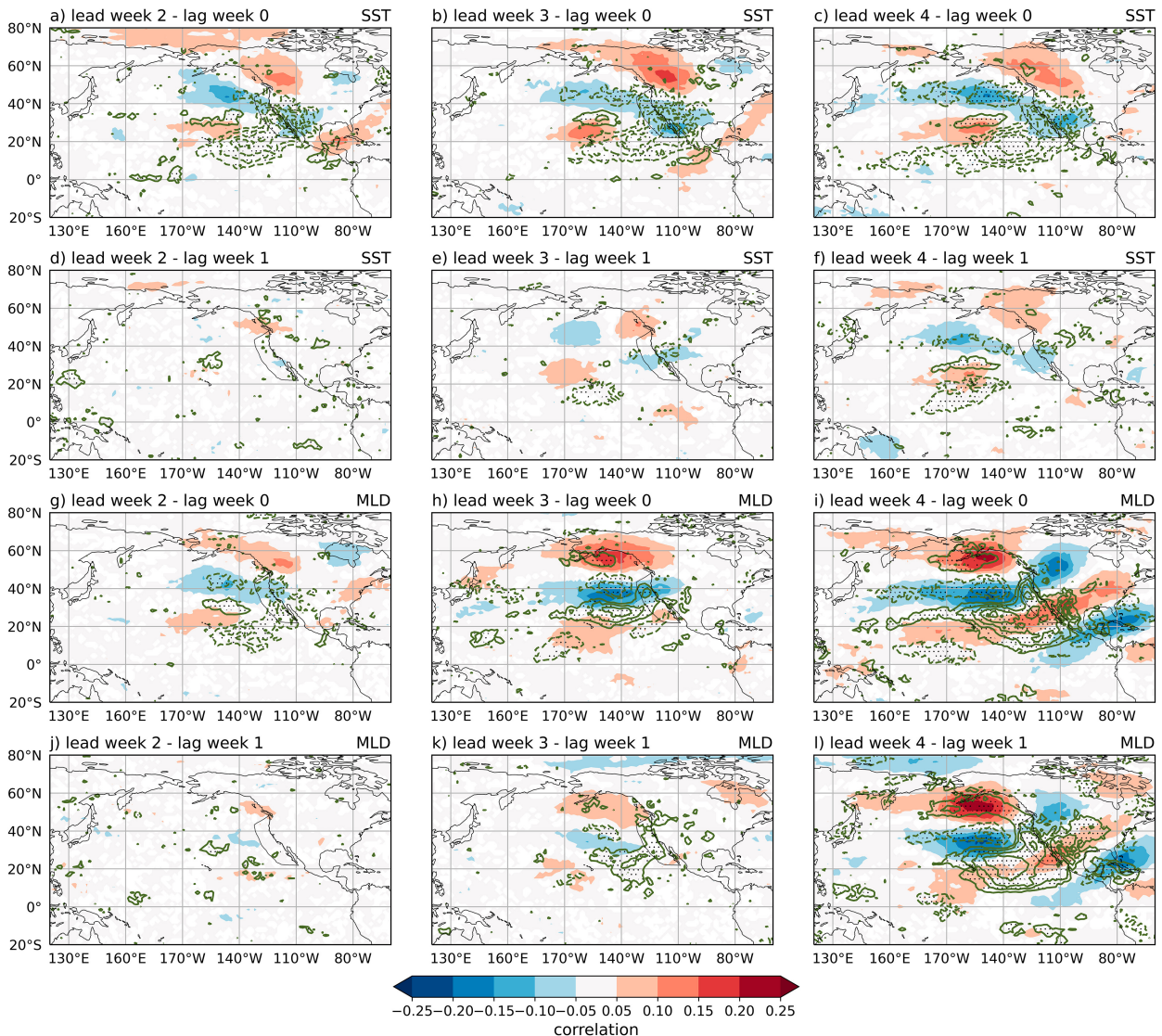


FIG. 5. As in Fig. 4, but for U200 (shading) and u^* (contours).

b. Conditional skill

Based on the ESA results, we condition the ensemble by selecting three good ensemble members with the smallest atmospheric AE(d, w, n) over the sensitive region at lead time 1d4d (the first 4 days of the forecast). Respectively, for the poor ensemble members, we select the three members with the largest atmospheric AE(d, w, n) over the sensitive region at lead time 1d4d. Conditional skill in terms of absolute error and pattern correlation is then computed for the ocean variables in the CCS for the good and poor ensemble members identified from the atmospheric errors.

We find a distinct relationship between good atmospheric forecasts in the sensitive region at earlier lead times and smaller errors in the CCS ocean state at later leads and correspondingly between poor atmospheric forecasts in the sensitive region at earlier lead times and larger errors in the CCS

(Fig. 6). Model bias is evident in the error curves from the nonzero error already present at lead 1d1d for both absolute error and pattern correlation (Figs. 6a,b,g,h). Good ensemble members at lead time 1d4d in Z500 and v10 decrease CCS AE_{SST} by 4%–5% in week 2 (Figs. 6c,e) and decrease CCS AE_{MLD} by 2%–3% during MJJ, although AE_{MLD} reduction is not statistically significant (Figs. 6d,f). Pattern correlation (PC) in the CCS during week 2 also improves when atmospheric errors are smaller at lead time 1d4d, especially for SST (Figs. 6i,k). Again, while MLD PC shows improvement for the good ensemble members, the differences are not statistically significant (Figs. 6j,l).

When plotting daily resolution of the conditional error (Fig. 7), we see that the error improvement for weeks 3/4 is mainly due to week 3, with week 4 not showing much improvement. Conditioning on v10, which has a more direct

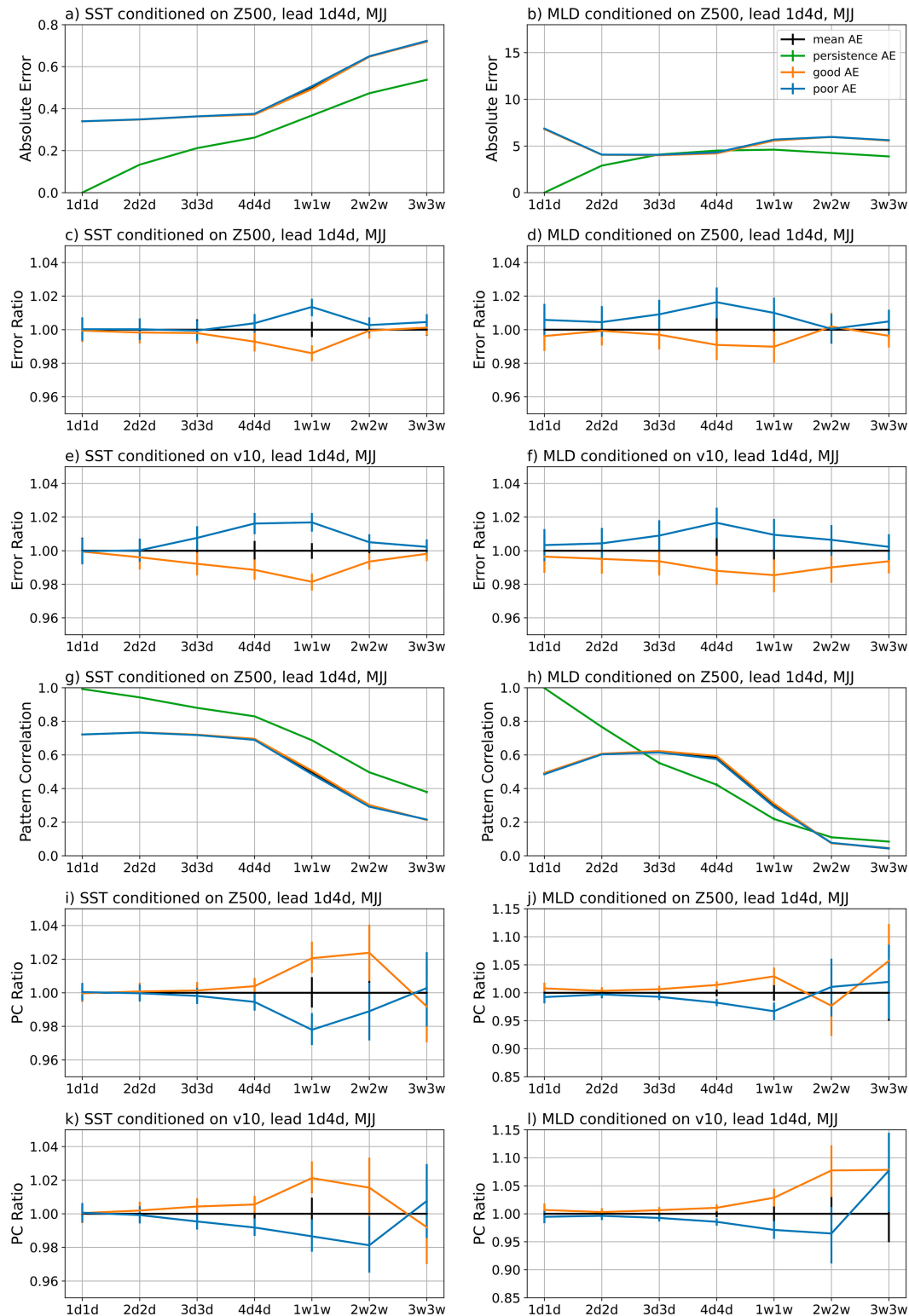


FIG. 6. AE during MJJ in the CCS for (a) SST and (b) MLD. Conditional error on 1d4d Z500 for (c) SST and (d) MLD and v10 for (e) SST and (f) MLD. Conditional errors are shown as ratio to the mean AE (black lines), error ratio of the three good (orange), and error ratio of the three poor ensemble members (blue). AE of damped persistence (green) are shown in (a) and (b). PC during MJJ in the CCS for (g) SST and (h) MLD. Damped persistence PC is shown in green. Conditional PC on 1d4d Z500 for (i) SST and (j) MLD and v10 for (k) SST and (l) MLD. Skill is evaluated using GLORYS verification.

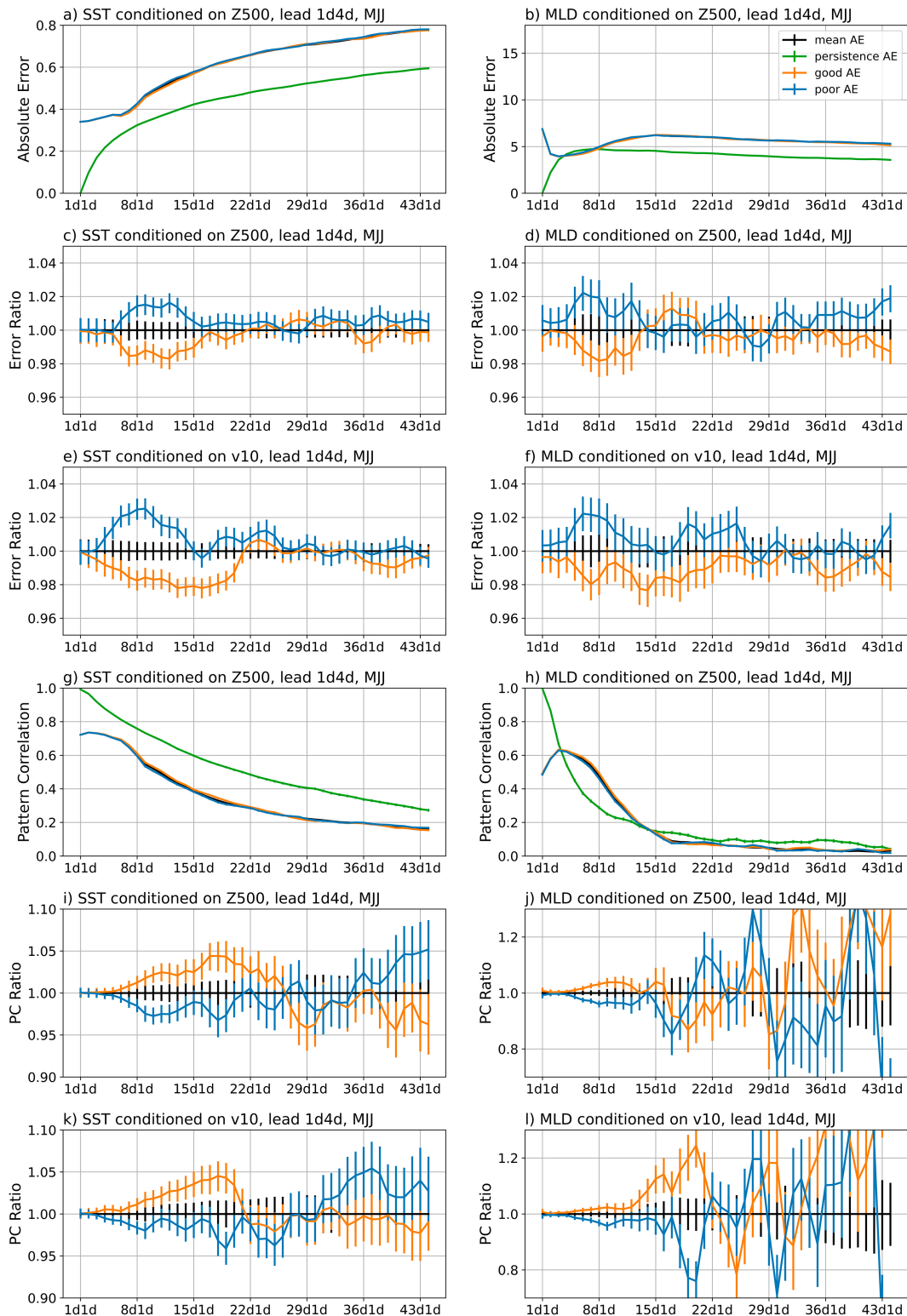


FIG. 7. AE during MJJ in the CCS for (a) SST and (b) MLD. Conditional error on 1d4d Z500 for (c) SST and (d) MLD and v10 for (e) SST and (f) MLD. Conditional errors are shown as ratio to the mean AE (black lines), error ratio of the three good ensemble members (orange), and error ratio of the three poor ensemble members (blue). The AE of damped persistence (green) are shown in (a) and (b). PC during MJJ in the CCS for (g) SST and (h) MLD. Damped persistence PC is shown in green. Conditional PC on 1d4d Z500 for (i) SST and (j) MLD and v10 for (k) SST and (l) MLD. Skill is evaluated using GLORYS verification.

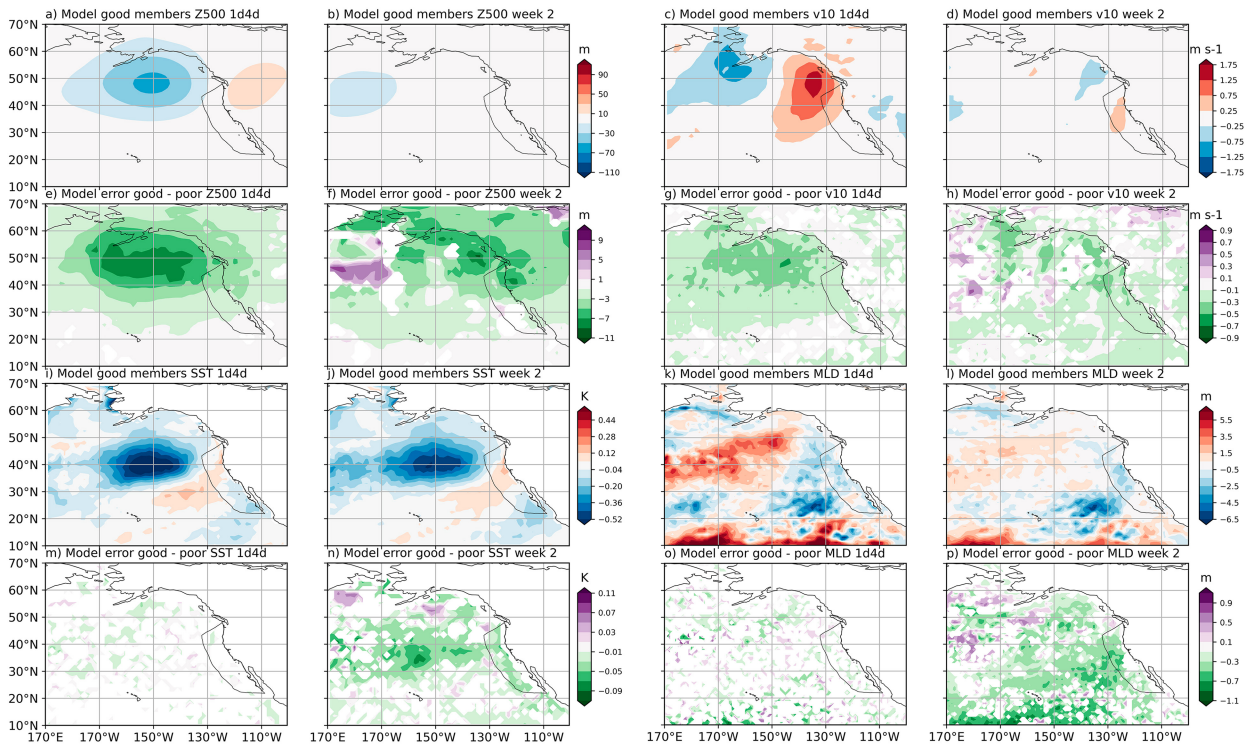


FIG. 8. Composites conditioned on negative Z500 anomalies at day 1 of the forecast during MJJ and the good three ensemble members with the smallest Z500 AE at lead 1d4d in the region 20°–60°N, 170°–130°W for Z500 (a) 1d4d and (b) 1w1w and v10 (c) 1d4d and (d) 1w1w and difference in model error between the good three and poor three ensemble members for Z500 (e) 1d4d and (f) 1w1w and v10 (g) 1d4d and (h) 1w1w. Composite of the good three ensemble members for SST (i) 1d4d and (j) 1w1w and MLD (k) 1d4d and (l) 1w1w and difference in model error between the good three and poor three ensemble members for SST (m) 1d4d and (n) 1w1w and MLD (o) 1d4d and (p) 1w1w. Green shading indicates smaller errors for the good ensemble members. The outline of the CCS is drawn in black in each panel.

impact on upper-ocean variability than Z500, in general has a longer and larger impact on CCS errors than Z500. Error and PC improvements tend to be largest in week 3 for v10 conditioned ensemble members (Figs. 7e,f,k,l). For example, SST PC improves by 2% for the good members in 1w1w and close to 3% in week 3 (Fig. 7k), and MLD PC improvement in week 3 is 18% (Fig. 7l) when conditioned on v10.

We also compare model skill to damped persistence and find that model CCS SST forecasts have larger errors than damped persistence for all lead times (Fig. 6a). For MLD, model errors are smaller than errors using damped persistence after day 3 (Fig. 6b and Fig. S2b).

4. Discussion

The sensitivity analysis results (Fig. 4) imply a potential physical mechanism for the influence of atmospheric anomalies on CCS ocean errors, consistent with previous work (Barth et al. 2007): Low pressure systems over the North Pacific drive anomalous poleward surface winds along the coast and reduced upwelling, while high pressure systems increase equatorward surface winds and enhance upwelling in the CCS. Errors in the atmospheric circulation can, therefore, influence the simulated timing of the upwelling and its strength

and lead to erroneous SST, MLD, and SSH forecasts. Changes in the atmospheric circulation lead to sea level pressure changes; this in turn influences near-surface winds. The changes in near-surface winds impact surface heat fluxes, which affect SST and MLD and likely play an important role in the open ocean.

To investigate this potential physical mechanism further, we consider the difference in error evolution between the good and poor ensemble members during MJJ for initial dates where Z500 is negative over the region 20°–60°N, 170°–130°W (Fig. 8).

While ensemble-mean model Z500 anomalies are in the right location, they are weaker than ERA5 (Figs. 8a and 9a). SST model anomalies are also in the correct location (Fig. 8i) but showing an overall cold bias in the model SSTs over the central North Pacific, the Gulf of Alaska, and the northern part of the CCS, while the model has a slight warm bias in the central CCS (Figs. 9i,j). Ensemble members with the smallest Z500 error at lead 1d4d have smaller Z500 errors over the Gulf of Alaska region, which persists until week 2. This reduction in error in Z500 goes along with a smaller error in v10 (Figs. 8e,f,g), which results in enhanced northward alongshore winds over the northern part of the CCS for the best ensemble members (Fig. 9g). The same ensemble members have slightly smaller errors in SST at lead 1d4d over the central

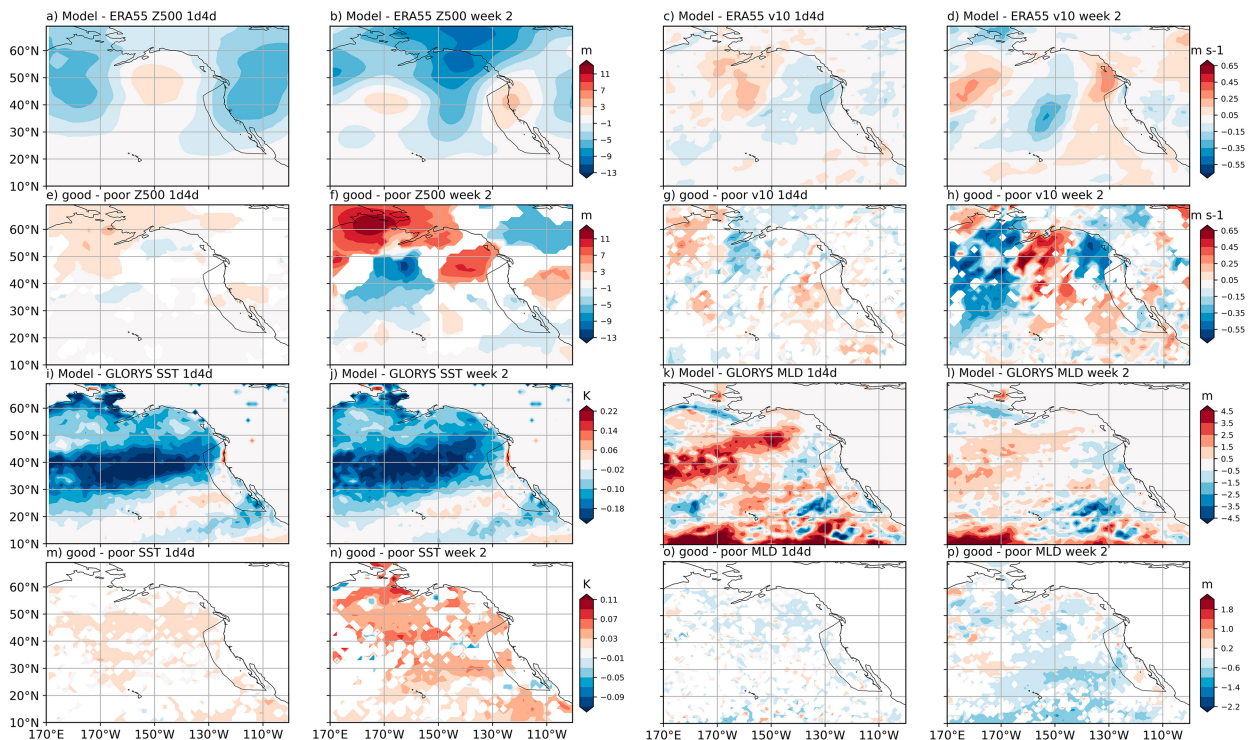


FIG. 9. Composites of Z500, v10, SST, and MLD conditioned on negative Z500 anomalies at day 1 of the forecast in the region 20°–60°N, 190°–230°E during MJJ. Model bias for Z500 at lead (a) 1d4d and (b) week 2, v10 at lead (c) 1d4d and (d) week 2, SST at lead (e) 1d4d and (f) week 2, and MLD at lead (g) 1d4d and (h) week 2. Bias difference between the three good and three poor ensemble members based on Z500 error at lead 1d4d in the region 20°–60°N, 190°–230°E is shown for Z500 at lead (e) 1d4d and (f) week 2, v10 at lead (g) 1d4d and (h) week 2, SST at lead (m) 1d4d and (n) week 2, and MLD at lead (o) 1d4d and (p) week 2. The outline of the CCS is drawn in black in each panel.

North Pacific, and that reduction in error extends into lead week 2 with smaller errors in the northern and southern part of the CCS as well (Figs. 8m,n). A reduction in error at week 2 is also apparent in MLD (Fig. 8p), mainly over the northern part of the CCS. Error reduction in both SST and MLD due to better atmospheric forecasts is overall stronger in the northern CCS.

Modeled MLD is too deep in the Gulf of Alaska (Figs. 9k,l). Good ensemble members (based on Z500 error at 1d4d) reduce the bias in the Gulf of Alaska and the northern and central CCS and retain these smaller errors out to week 2 (Figs. 9o,p). Patterns of bias differences between good and poor members are complementary for SST and MLD (with opposite signs) (Figs. 9n,p).

Taking the atmospheric and oceanic errors together, the good ensemble members have a deeper low pressure signal at early lead times over the Gulf of Alaska and a stronger poleward atmospheric flow near the surface along the west coast of North America (Figs. 8a,c), both of which act to reduce the model bias in those respective regions. This leads to a smaller negative SST bias in the northern CCS in the good ensemble members and a reduction in the absolute error at later lead times (Figs. 8n,p). Good ensemble members show warmer SST anomalies and shallower MLD in the northern part of the CCS, consistent with the increased northward alongshore

winds over the northern part of the CCS. During this time of year, this would potentially be accompanied by a temporary reduction in upwelling in the CCS (Barth et al. 2007).

Compositing on positive Z500 anomalies in the region 20°–60°N, 170°–130°W at 1d4d is almost analogous (Fig. S2). The good ensemble members have a stronger high pressure system in the Gulf of Alaska and stronger equatorward surface winds along the west coast of North America north of the CCS. Good ensemble members again have larger SST anomalies than poor members, alleviating the cold bias in the model and leading to smaller SST errors at later lead times.

Forecast skill in the CCS can conceivably be influenced by other factors as well, such as the strength of local atmosphere–ocean coupling in the model or the state of large-scale climate modes. Local coupling might modestly affect the southern CCS, particularly in week 2, although the difference in estimated coupling strength is not statistically significant (Fig. 10). Here, coupling strength is estimated by regressing v10 against SST and MLD at each grid point in both model and verification. This is done for subsets of 90% of initial dates and repeated 100 times. This results in a distribution of regression coefficients at all grid points. The difference between model and verification regression is deemed significant if the 5th–95th percentile intervals do not overlap. The southern CCS shows little improvement, though averaging over the southern domain might

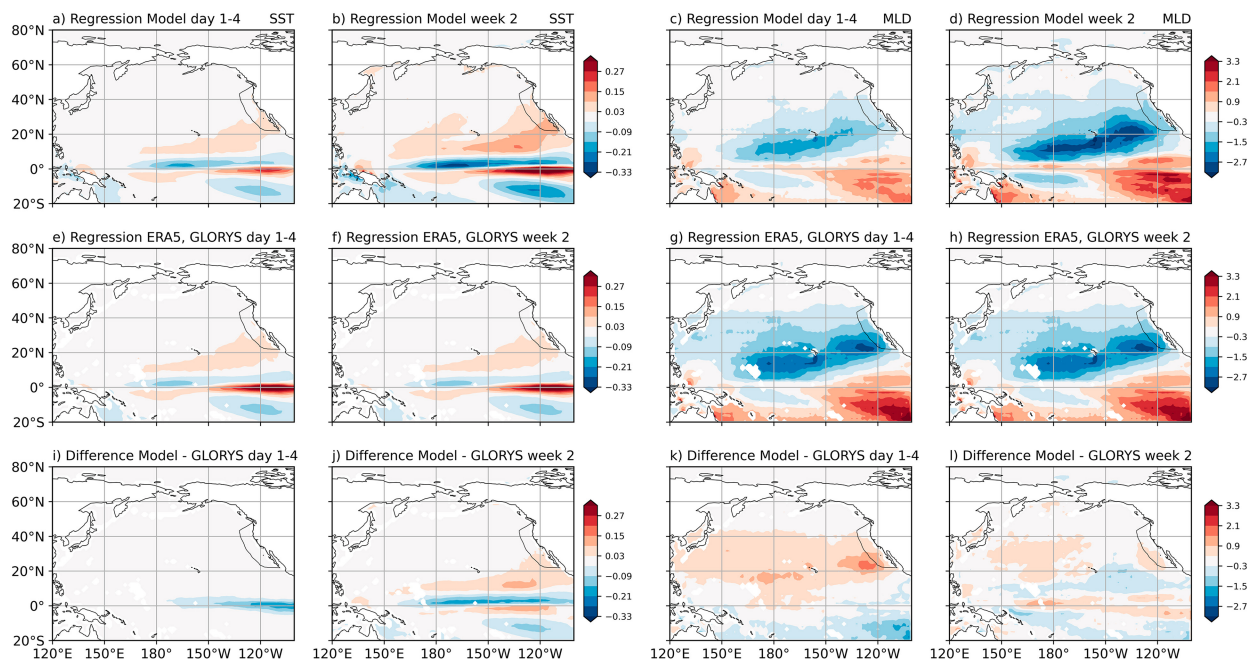


FIG. 10. Maps of regression coefficients of concurrent v_{10} onto SST and MLD. Model regression for v_{10} and SST at lead (a) 1d4d and (b) week 2 and v_{10} and MLD at lead (c) 1d4d and (d) week 2. ERA5 v_{10} and GLORYS SST at lead (e) 1d4d and (f) week 2 and ERA5 v_{10} and GLORYS MLD at lead (g) 1d4d and (h) week 2. Difference between model and ERA5/GLORYS regression for v_{10} and SST at lead (i) 1d4d and (j) week 2 and v_{10} and MLD at lead (k) 1d4d and (l) week 2. Locations where the differences are statistically significant are stippled. The differences are not significant at any point. See section 2c(3) for details on the statistical significance calculation.

indicate slight improvement and long-lead predictability was shown in Cluett et al. (2024). We found no dependence in ocean error differences when further conditioning on modes of variability (ENSO, the Pacific meridional mode, the North Pacific Gyre Oscillation, the Pacific–North American pattern, and the MJO) at initialization (Fig. 11). This indicates that errors in the representation of low frequency modes of climate variability are likely not the main driver of CCS ocean errors on the time scales of interest here, although they can be on longer time scales (Cluett et al. 2024).

Additionally, coastally trapped waves (CTWs) may offer a source of predictability on S2S time scales. CTWs can originate from equatorial Kelvin waves propagating poleward along the coast or be induced by wind alterations within or immediately south of the CCS. Given that the most significant wind discrepancies here are localized to the northern part of the domain, CTWs may not substantially influence the distinctions between good and poor forecasts in this region but can be important further equatorward. These waves move relatively fast and can move up the coast on the time scale of weeks.

Apart from physical processes, the particular coupling strategy of the IFS CY47R3 could also impact the results shown here. During the first 4 days of the model forecast, SSTs are only partially coupled to the atmosphere in that the initial SSTs are used together with the forecast SST tendencies; after day 4 until day 8, the partial coupling is gradually reduced,

and after day 8, the model ocean and atmosphere are fully coupled (ECMWF 2021).

5. Conclusions

In this study, we show that early atmospheric forecast errors are positively related to ocean forecast errors at later lead times in the ECMWF S2S hindcasts. Using the ensemble sensitivity analysis applied to a coupled forecast system, we identify regions where conditioning forecasts on better atmospheric states at early lead times improves the forecasts of ocean state anomalies in the CCS at later lead times and conditioning on worse atmospheric states at early lead times degrades the forecasts of ocean state anomalies in the CCS.

It is hypothesized that ensemble members exhibiting smaller initial atmospheric errors provide more accurate forcing to the ocean during the initial week of the forecast, thereby resulting in more accurate oceanic states at subsequent lead times. In addition, there may be a small contribution of smaller ocean errors at initialization also leading to better ocean forecasts, but this effect lies outside the scope of the present investigation. Given that ocean improvements at initialization are a much smaller percentage compared to atmospheric improvements when conditioned on the best atmospheric ensemble members, the improvement in the ocean forecast is primarily attributed to improved atmospheric forcing. The underlying physical relationship is hypothesized as follows: Ensemble members with smaller errors in Z500

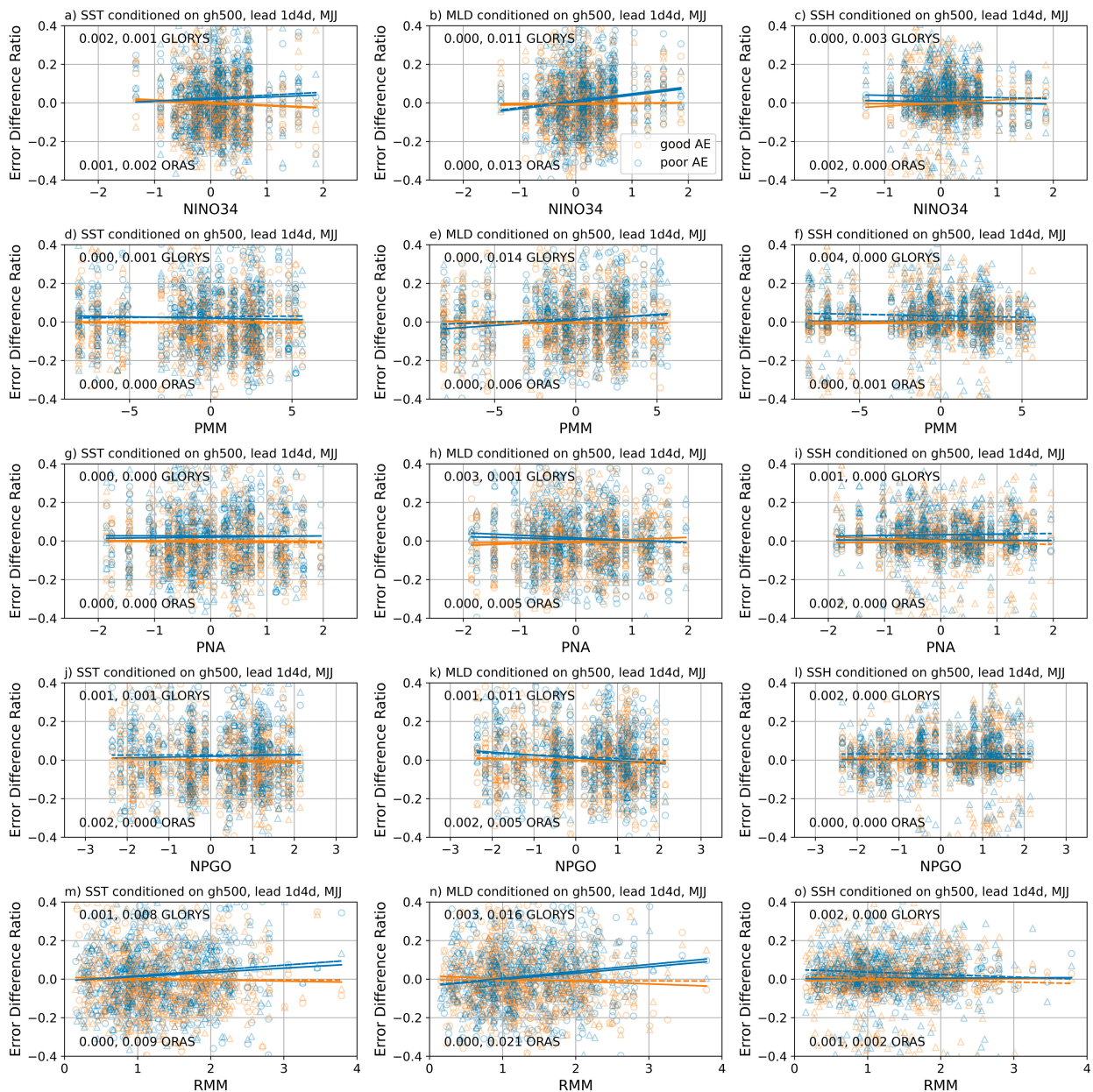


FIG. 11. Scatterplots of error difference ratio for the good (orange) and poor (blue) three ensemble members for (left) SST, (middle) MLD, and (right) SSH for Niño-3.4, PMM, PNA, NPGO, and RMM. GLORYS errors are plotted using circles, and ORAS5 errors are plotted using triangles. Also shown are the least squares regression lines for GLORYS (solid) and ORAS5 (dashed). The R values of the linear fit are given in each panel for the best and poorest members.

anomalies are associated with improved forecasts of v10 anomalies across the North Pacific, particularly along the North American Pacific coast and the northern extent of the CCS. This improvement in near-surface winds is posited to lead to more accurate wind forcing of the upper ocean along the coast, which consequently contributes to more accurate forecasts of SST and MLD in the CCS.

This analysis provides evidence for a previously underexplored physical pathway of error propagation in the coupled model system: Early lead-time atmospheric circulation errors

impact ocean forecasts in weeks 1–2, leading to larger ocean errors. The model consistently underestimates atmospheric and oceanic anomaly amplitudes compared to observations. The spatial structure and sign of these anomalies are well represented in both components of the system. This indicates not only that the model is able to somewhat reproduce the interaction and feedback between ocean and atmosphere, at least for ensemble members with small initial error, but also that the coupling is potentially too weak based on the regression coefficients. This also suggests that efforts to improve early

lead-time model errors in the atmosphere may improve longer lead-time upper-oceanic errors. While this study focused on the ECMWF S2S model and the CCS, the analysis framework can be extended for investigating other regions and other coupled models such as the NOAA Unified Forecast System.

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Data availability statement. The ECMWF S2S model output is available from the S2S database at <https://apps.ecmwf.int/datasets/data/s2s-reforecasts-daily-averaged-ecmf/levtype=sfc/type=cf/> (Vitart et al. 2017). Documentation for the IFS model version used can be found at <https://www.ecmwf.int/en/publications/ifs-documentation>. The original S2S database is hosted at ECMWF as an extension of the TIGGE database. The ERA5 reanalysis data are available from the Copernicus Climate Change Service (C3S) Data Store (CDS) (Hersbach et al. 2017) at <https://cds.climate.copernicus.eu/datasets/reanalysis-era5-single-levels?tab=overview>. GLORYS and ORAS5 reanalysis data are freely available from Copernicus Marine Service Information (European Union-Copernicus Marine Service 2018, 2019) at <https://data.marine.copernicus.eu>. The Python code used for the analysis presented here is archived at https://github.com/mgehne/Code_Wks34_ESA_CondError_CCS.git. This work is based on S2S data. S2S is a joint initiative of the World Weather Research Programme (WWRP) and the World Climate Research Programme (WCRP). The original S2S database is hosted at ECMWF as an extension of the TIGGE database.

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