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Key Points:

- Large-scale circulation differences across the Pacific Basin are predictable, but California precipitation has high internal variability
- Higher skill in predicting upper-level (200 mb) circulation anomalies relative to the lower-level (850 mb) anomalies over the Pacific Basin
- Ensemble subset with correct Arctic Oscillation phase improves accuracy of predicting California precipitation differences between these seasons

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California Winter Precipitation Predictability: Insights From the Anomalous 2015–2016 and 2016–2017 Seasons

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Abstract The unexpected dry 2015–2016 El Niño winter and extremely wet 2016–2017 La Niña winter in California challenged current seasonal prediction systems. Using the Met Office GloSea5 forecast ensemble, we study the precipitation and circulation differences between these seasons and identify processes relevant to California precipitation predictions. The ensemble mean accurately predicts the midlatitude atmospheric circulation differences between these years, indicating that these differences were predictable responses to the strong oceanic forcing differences. The substantial California precipitation differences were poorly predicted with large uncertainty. Notable differences in high-latitude circulation anomalies associated with internal variability distinguish the ensemble members that successfully simulate precipitation from those that do not. Specifically, accurate representation of the Arctic Oscillation phase differences improves the accuracy of simulated precipitation differences but these differences were not well predicted in the ensemble mean for these seasons. Improved representation of high-latitude processes such as the Arctic Oscillation and polar-midlatitude teleconnections could therefore improve California seasonal predictions.

Plain Language Summary California recently experienced two unusual winter seasons. Following a failed rainy season despite the strong 2015–2016 El Niño that typically brings heavy rains, California unexpectedly experienced one of its wettest winter seasons on record during the 2016–2017 La Niña. The seasonal forecast systems were unable to predict these unusual winter precipitation patterns. We examine the ability of a state-of-the-art forecast system to capture the large-scale atmospheric circulation patterns that influence the track of storms, which bring a majority of winter precipitation to California. We show that the seasonal forecast systems can reproduce the large-scale circulation differences in the North Pacific-American domain, but random atmospheric variability can still easily prevent the accurate prediction of regional scale precipitation in extratropical regions such as California. Further, we identify the role of a natural pattern of large-scale variability in the atmosphere that affects weather in the middle and high latitudes, referred to as the Arctic Oscillation, in controlling the accuracy of California precipitation forecasts. Prioritizing improvements in the representation of these patterns, the processes by which they are predicted and their influence over other regions in the forecasts systems can help improve seasonal predictions, which is important for the management of California's water resources and infrastructure.

1. Introduction

The recent winters of 2015–2016 and 2016–2017 were particularly anomalous for California. Despite an exceptionally strong El Niño event in 2015–2016 (L'Heureux et al., 2016) that was expected to produce heavy rains (Chen & Kumar, 2018; Cohen et al., 2017; Swain et al., 2016) and to ameliorate the prolonged 2012–2016 drought (Seager et al., 2015; Swain et al., 2014; Wang et al., 2014), the winter season was close to normal for Northern California and below normal for Southern California (Jong et al., 2018). In contrast, 2016–2017 was the second wettest year on record despite the presence of weak La Niña conditions in the Pacific (Lee et al., 2018). A few intense winter storms, known as atmospheric river events, accounted for most of the precipitation during the 2016–2017 season (Wang, Yoon, et al., 2017). These had severe impacts across the state including flash flooding, mudslides, and strong winds that caused extensive damage to bridges, dams, homes, and other infrastructure and forced evacuations of over a hundred thousand people (Smith et al., 2018).

Accurate seasonal forecasts, therefore, have important consequences for resource and emergency management in California. The 2015–2016 forecasts of a wet California winter were largely based on the canonical influence of El Niño. However, the reliability of the influence of El Niño on California precipitation is sensitive to factors such as their intensity, spatial characteristics, and timing (e.g., Hoell et al., 2016; Jong et al., 2016; Lee et al., 2018; Wanders et al., 2017). Large internal atmospheric variability on regional scales can also preclude the ability to produce skillful forecasts despite strong sea surface temperature (SST) forcing (e.g., Chen & Kumar, 2018; Jong et al., 2018; Kumar & Chen, 2017). In the 2015–2016 season for which observations differ substantially from the ensemble mean forecasts, internal variability was found to have a larger influence on California precipitation than the forcing from the prevailing SST pattern (Chen & Kumar, 2018; Jong et al., 2018; Wang, Anichowski, et al., 2017). In addition, while the difficulty of ensemble forecasts to predict the extreme wetness in parts of California in 2016–2017 could simply be a result of the rarity of the event, it also highlights the possibility that the current forecast models may either underestimate internal variability or have an inaccurate representation of predictable processes such as the influence of Arctic forcings (Cohen et al., 2017) or midlatitude blocking (Wanders et al., 2017) that are relevant for precipitation over this region.

California receives the bulk of its precipitation from short-lived midlatitude storms during the winter months (Dettinger, 2013; Swain et al., 2016). This makes it sensitive to the large-scale circulation patterns that can influence the location of the jet stream over the North Pacific (Cayan & Roads, 1984; Seager et al., 2015; Swain et al., 2016; Wang et al., 2014). These anomalous seasons of 2015–2016 and 2016–2017 that had large differences in circulation patterns and seasonal precipitation provide a test bed for identifying such relationships for the purpose of improving predictions. Here we examine the predictability of the relevant large-scale circulation patterns, their association with California precipitation, and the role of other remote factors in driving the precipitation shift between the 2015–2016 and 2016–2017 seasons. Using the high-resolution UK Met Office Global Seasonal Forecast System version 5 (GloSea5), we show that high skill in predicting the seasonal circulation differences over the Pacific does not necessarily translate to accurate forecasts of the precipitation differences between these years. However, accurate simulations of high-latitude circulation patterns have an important role in shaping the precipitation differences between these seasons. Our findings suggest that efforts to improve the representation and prediction of high-latitude processes could improve the prediction skill of precipitation in California.

2. Data and Methods

For observed precipitation, we use the Climate Prediction Center Global Unified Gauge-Based Analysis of Daily Precipitation data at a spatial resolution of 0.5° × 0.5° (Chen, Wei et al., 2008; Chen, Xie, et al., 2017; Xie et al., 2007). Monthly geopotential heights (GPH) and sea level pressures (SLP) are from the ERA-Interim Reanalysis data set by the European Center for Medium-Range Weather Forecasting (Dee et al., 2011).

To examine the differences in winter (DJF) precipitation and circulation patterns, we analyze the 20-member forecast ensembles for 2015–2016 and 2016–2017 winter seasons from the UK Met Office GloSea5 (MacLachlan et al., 2015). The GloSea5 system includes the coupled Hadley Center Global Environmental Model version 3 with an atmospheric resolution of 0.83° longitude by 0.55° latitude and 85 quasi-horizontal levels and a uniform ocean resolution of 0.25° longitude by 0.25° latitude and 75 quasi-horizontal levels. This high-resolution atmosphere and ocean model configuration reduces biases relative to coarser-resolution models in representing important physical processes affecting the midlatitudes and demonstrates high prediction skill for natural modes of variability such as El Niño–Southern Oscillation, North Atlantic Oscillation (NAO), and the Arctic Oscillation (AO; MacLachlan et al., 2015; Scaife et al., 2014). The ensemble members of the winter forecasts are initialized on 10 dates centered around 1 November. Members initialized on the same dates differ only in the stochastic physics perturbations (Arribas et al., 2010). Initial atmospheric and land-surface conditions for the forecast system were taken from ERA-Interim reanalysis, and initial ocean conditions and sea-ice concentrations were from the Forecasting Ocean Assimilation Model system. Additional details of the GloSea5 prediction system can be found in MacLachlan et al. (2015). GloSea5 produced a successful forecast of the 2015–2016 El Niño and the Atlantic circulation anomaly (Scaife, Comer, Dunstone, Fereday, et al., 2017) but has not been examined for the Pacific sector.

Examining seasonal differences allows us to focus on the dramatic shift in precipitation between the two winters and avoids the need to correct for any forecast drifts in GloSea5. Forecast ensemble means are considered the response to SST forcing, and the variations between ensemble members are considered to represent internal atmospheric variability. While evaluating the difference in various climate variables between the two winter seasons, we treat each member of each forecast ensemble independently. Therefore, the ensembles of potential differences between 2016–2017 and 2015–2016 are calculated from any two ensemble members in the 20-member forecasts for each season, yielding 400 difference pairs. We use spatial correlations to evaluate the similarity in the simulated and observed patterns of each variable for each of these 400 possible outcomes.

3. Predictions of California Seasonal Precipitation and Large-Scale Circulations

In 2016–2017, the average winter rainfall across northern and southern California was heavier than in 2015–2016 (Figures 1a–1c). GloSea5 ensemble mean forecasts simulate slightly wetter conditions over northern California in 2016–2017 than 2015–2016, but the simulated mean differences between the two seasons were ~12% of the magnitude of the observed differences (Figures 1d–1f). For northern California, the observed regional-average precipitation was underestimated in both seasons (red diamonds in the box plot) but the forecasts did capture heavier rainfall in 2016–2017 relative to 2015–2016, although with lower magnitude than observed (Figures 1g–1i). In contrast, the median difference in forecasts for southern California is indistinguishable from zero while rainfall was overestimated in 2015–2016 and underestimated in 2016–2017 (Figures 1g–1i). Despite the expectation of a stronger influence of El Niño on southern California relative to northern California (Jong et al., 2016), the strong 2015–2016 El Niño did not result in forecasts of substantially higher rainfall over the region relative to 2016–2017. While the differences between 2015–2016 and 2016–2017 winter seasons for northern and southern California are within the range of the forecasts (Figure 1i), they lie in the tails of the distribution, suggesting that either internal atmospheric variability in precipitation largely overwhelmed any forced signal in response to the SST differences or that the predictable shift in rainfall was underestimated.

In contrast to the precipitation forecasts, the large-scale atmospheric circulation patterns over the northern Pacific were forecast with a high degree of accuracy (Figure 2). At the upper level (200 mb), there was anomalously high GPH in the northern-central Pacific and anomalously low GPH across much of the tropical and subtropical Pacific in 2016–2017 relative to the 2015–2016 winter (Figure 2a). This dipole pattern resulted from the anomalous high pressure over the North Pacific in response to the weak La Niña in 2016–2017 and the deepening of the Aleutian Low and warming of the tropical atmosphere in response to the El Niño in 2015–2016 (e.g., Bjerknes, 1969; Seager et al., 2010; Trenberth et al., 1998). This GPH pattern indicates a relatively northward shifted position of the Pacific storm track in 2016–2017 relative to 2015–2016. In addition, the opposite GPH dipole over North America guided the storm tracks toward California in 2016–2017 relative to the previous winter. GloSea5 accurately captured the overall trough-ridge-trough-ridge over the North Pacific and western North America (Figure 2b). In particular, the spatial correlation between the ensemble mean forecast and the observed differences between 2016–2017 relative to 2015–2016 over the Pacific (Figure 2a) was 0.89 (Figure 2b). The forecast ensemble spread in the correlations with the observed differences largely exceeded 0.5 (Figure 3a).

In the lower troposphere (850 mb), GPH anomalies are largest in the midlatitudes with an anomalous low-high pattern across the Pacific in the 2016–2017 season relative to 2015–2016 (Figures 2c and 2d). The GloSea5 ensemble mean also closely represents this observed pattern with spatial correlations of the ensemble mean circulation anomalies over the Pacific exceeding 0.8 (Figure 2d), albeit with a relatively larger spread in correlations within the ensemble than for the 200-mb correlations (Figure 3a). The greater spread and the somewhat lower ensemble mean correlation at the lower-level indicates that the model has relatively higher skill in predicting the upper-level circulation differences relative to the lower level. This is consistent with an upper-tropospheric source of the predictable signal in the extratropics (e.g., Scaife, Comer, Dunstone, Knight, et al., 2017). Despite the high correlations in the ensemble means of the 200- and 850-mb GPH patterns, the ensemble mean correlation between the spatial pattern of precipitation differences in GloSea5 and in observations is ~0.5 with a wide ensemble spread that spans zero (Figure 3a). Together, these results suggest that despite simulating the large-scale midlatitude atmospheric circulations with a high degree of accuracy, the ensemble shows large uncertainty and low prediction skill in simulating the precipitation differences between these seasons. Either due to internal variability or model biases in capturing the forced response, smaller-scale features such as the anomalously low 850-mb GPH anomalies over the western United States

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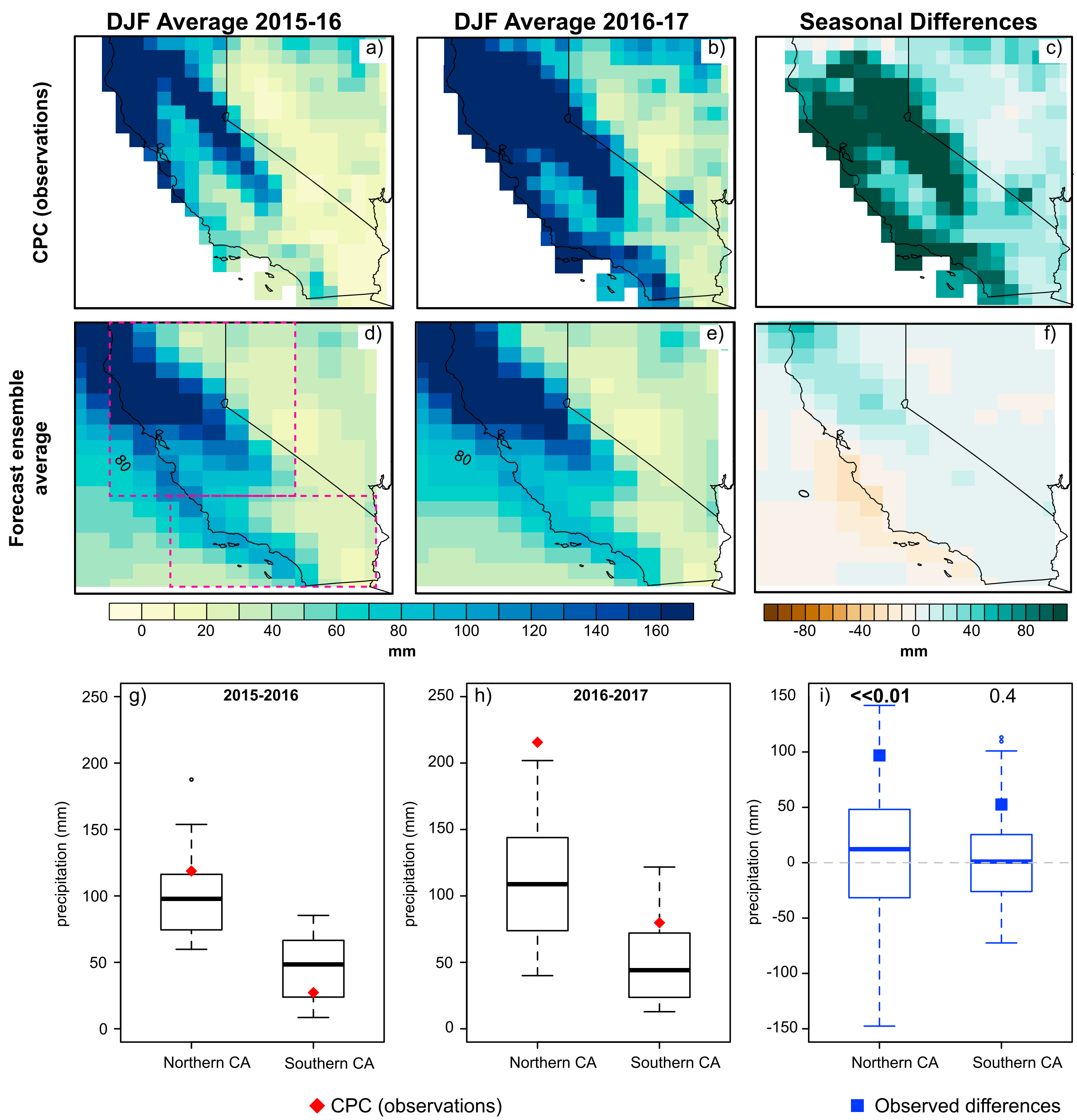

Figure 1. Observed and simulated precipitation: California winter season (DJF) average rainfall for 2015–2016 and 2016–2017 from the (a and b) NOAA Climate Prediction Center observations and (d and e) UK Met Office seasonal forecast system ensembles. (c) Observed and (f) forecast differences in rainfall between 2016–2017 and 2015–2016 seasonal averages. The box plots show the area-average seasonal (g and h) precipitation and (i) precipitation differences in the ensemble forecast over northern and southern CA (red boxes in panel a). Numbers in panel (i) indicate the *p*-value from the one-sample *t* test that examines the null hypothesis that the forecast ensemble mean of regional precipitation differences between the two seasons is zero. The boxes represent the 25th/75th percentile, the whiskers represent the 5th/95th percentile, and the dots represent outliers of the distribution.

that were not captured in the GloSea5 ensemble mean and subtle differences in the strength and location of the upper-level GPH anomalies likely contributed to the lower prediction skill of the precipitation forecasts.

4. Influence of Mid-Latitude and High-Latitude Circulation on California Precipitation

To identify the circulation features that are relevant for accurate forecasts of precipitation, we contrast the ensemble members that have spatial correlations with observed precipitation differences lying in the

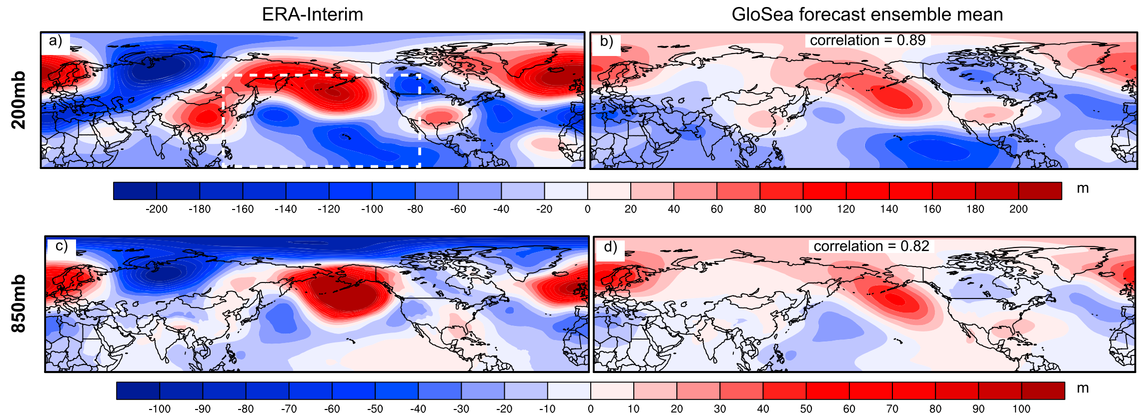

Figure 2. Observed and simulated circulation patterns: Difference in (a and b) 200-mb and (c and d) 850-mb seasonal (DJF) mean geopotential heights between 2016–2017 and 2015–2016 in ERA-Interim reanalysis and the GloSea forecast ensemble. Correlations in (b) and (d) refer to the spatial correlation in geopotential height differences in ERA-Interim and the forecast ensemble mean over the Pacific basin (white box in panel a).

highest ("successful") and lowest ("unsuccessful") fifth percentiles of the distribution (Figures 4a and 4b). The "successful" subset of ensemble members reproduces the magnitude and spatial pattern of precipitation differences between winter 2015–2016 and 2016–2017 and have correlations with observations exceeding 0.8 (Figures 1c and 4a). The "unsuccessful" subset has opposite precipitation anomalies of similar magnitudes across the domain and spatial correlations with observations exceeding −0.8.

There are two notable differences in the circulation patterns in the middle and high latitudes between these ensemble subsets that explain these contrasts in precipitation patterns (Figures 4c–4f). First, the anomalous high in the North Pacific in the "successful" members lies over the region of the Aleutian Low along with an anomalous low over the U.S. west coast (Figures 4c and 4e). This configuration represents a weakening of the climatological ridge over the northeast Pacific and directs the storm tracks toward California, consistent with

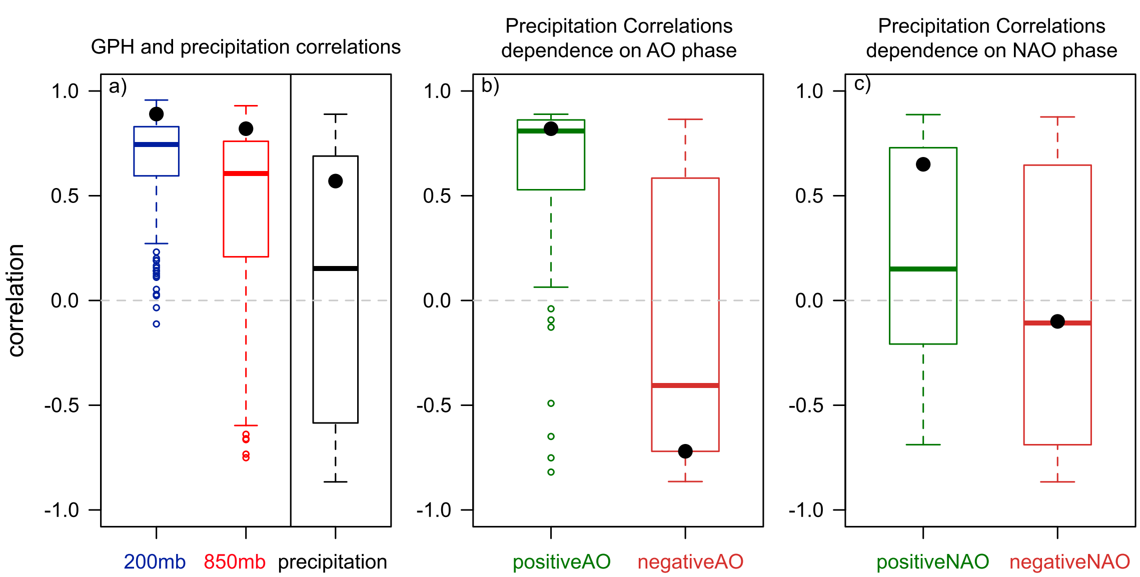

Figure 3. Relationship between circulation patterns and precipitation: Box plots showing the distribution of correlations between model forecast and observed differences between 2016–2017 and 2015–2016 in (a) 200-mb and 850-mb geopotential heights (GPH) over the Pacific domain (shown in Figure 2a) and precipitation over California. In the box plots, the boxes represent the 25th/75th percentiles and the whiskers represent the 5th/95th percentiles of the ensemble distribution. Observed GPH refers to ERA-Interim reanalysis, and observed precipitation refers to Climate Prediction Center data. The heavy dots are the spatial correlations between the GloSea5 ensemble mean of each variable with the corresponding observations. (b and c) Range of spatial correlations between model and observed precipitation for ensemble members that have positive or negative phases of the Arctic Oscillation (AO) and the North Atlantic Oscillation (NAO). Positive and negative AO/NAO phases are defined based on the standardized AO/NAO index exceeding ±1. The black dots in (b) and (c) are correlations of the ensemble mean precipitation patterns of the respective subsets with the observed precipitation.

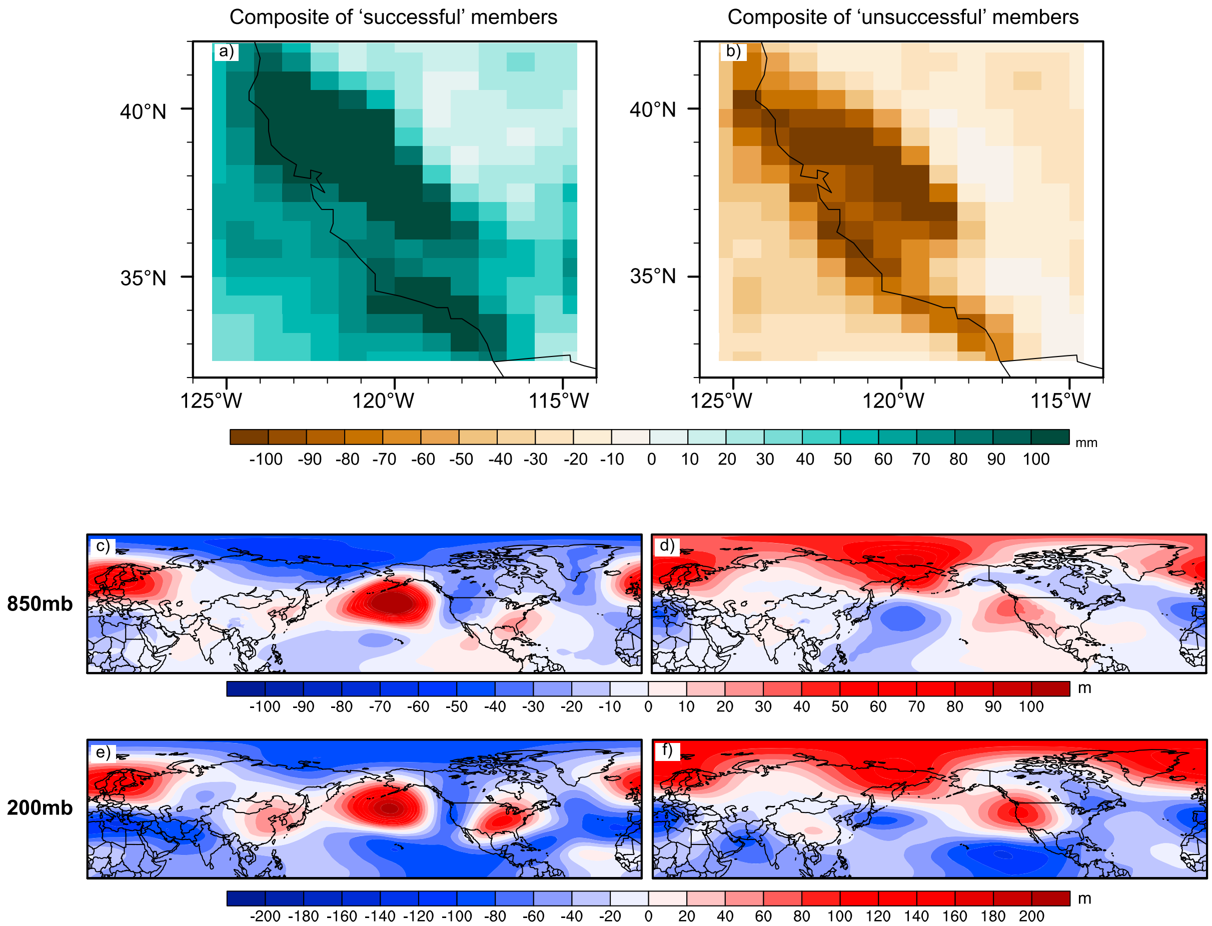

Figure 4. Successful and unsuccessful forecasts: Composite differences between the 2015–2016 and 2016–2017 winter season (a and b) precipitation, (c and d) 850-mb geopotential heights, and (e and f) 200-mb geopotential heights for the fifth percentile of ensemble members with the (left) highest and (right) lowest correlations with observed (Climate Prediction Center) precipitation differences.

the composite precipitation pattern that shows widespread wetness across California (Figure 4a). In contrast, the ridge is centered over the U.S. west coast in the "unsuccessful" subset, which is unfavorable for storms to reach California, and consistent with widespread dry conditions across California (Figures 4b, 4d, and 4f). Second, seasonal GPH across the Arctic are anomalously low in the "successful" subset and anomalously high in the "unsuccessful" subset at both levels. These differences indicate substantially different conditions in the Arctic between these two seasons. Consistent with the observed anomalously low GPH in the Arctic (Figures 2a and 2c), the pattern of GPH anomalies in the composite of the "successful" subset indicates a stronger polar vortex in 2016–2017 relative to 2015–2016 representing a more positive AO phase (Figures 4c and 4e), whereas the pattern of GPH anomalies in the composite of the "unsuccessful" subset represents a more negative AO phase (Figures 4d and 4f).

Given the contrasting anomalies in the high latitudes between the "successful" and "unsuccessful" subset, we examine the influence of the AO phase in simulating accurate precipitation differences between these two seasons (Figure 3b). To do so, we define the AO index as the area-weighted mean SLP differences between 35–55°N and 60–90°N, following MacLachlan et al. (2015). We standardize the AO index using the standard deviation of the GloSea5 ensemble and subset the ensemble based on values of the standardized AO index exceeding ±1. Conditioning the spatial correlations of model and observed precipitation differences on the AO phase suggests that accurately simulating the AO phases has a strong influence on the accuracy of precipitation simulations (Figure 3b). A majority of ensemble members with positive AO phases in 2016–2017 relative to 2015–2016 have strongly positive model-observed precipitation correlations. This subset has a median correlation of ~0.8 compared to a median correlation of ~0.15 for the entire ensemble (Figures 3a

Table 1
(a) AO Index: Area-Weighted Mean Sea Level Pressure Difference (Pa) Between 35–55°N and 60–90°N in Each Year and Their Difference in ERA-Interim and the Ensemble Mean of GloSea5; And (b) NAO Index: Area-Weighted Mean Sea Level Pressure Difference (Pa) Over the Domains of (50°W–10°E, 25–55°N) and (40°W–20°E, 55–85°N) in Each Year and Their Difference in ERA-Interim and the Ensemble Mean of GloSea5

		2015–2016	2016–2017	Difference
(a) AO Index	ERA-Interim	458.6	716.9	258.3
	GloSea5	386.7	238.5	−148.2
(b) NAO Index	ERA-Interim	1,749.6	1,369.2	−380.4
	GloSea5	1,632.5	1,196.4	−436.1

and 3b). With a few exceptions, the entire distribution of model and observed precipitation correlations for ensemble members with positive AO phases is positive and 95% of the subset ensemble has correlations exceeding 0.5, indicating a fairly accurate representation of the observed seasonal precipitation differences. In contrast, the median correlation between the model and observed precipitation for ensemble members with negative AO anomalies is ~−0.4 and its range spans −0.86 to 0.86. The wider spread in the precipitation correlations for the negative AO phase relative to the positive AO phase could indicate a larger uncertainty in the influence of the negative AO phase on California precipitation, at least in the presence of similar tropical forcing.

Only 9% of the 400 ensemble difference pairs simulate an anomalously positive AO phase (AO index >1 standard deviation) in 2016–2017 relative to 2015–2016. Further, the ensemble mean difference in the AO index between these seasons is negative, which is opposite to the observed anomalously positive difference in AO phase (Table 1). The ensemble mean GPH composite shows weak positive anomalies across the Arctic instead of the strongly negative anomalies in observations (Figure 2), which could explain the lower skill in the precipitation forecasts. Therefore, our results suggest that accurately forecasting the AO phase differences could be important for accurately predicting differences in California winter precipitation.

A similar analysis of the influence of the NAO phase (Figure 3c) suggests a relatively weaker and more uncertain effect on these seasonal California precipitation differences. The NAO was anomalously negative in 2016–2017 relative to 2015–2016, and this was correctly predicted in the GloSea5 ensemble mean (Table 1). 34% of the 400 ensemble difference pairs had a negative NAO phase (NAO index >1 standard deviation) relative to the 4% that had a positive phase. However, the ensemble members that simulated the observed negative NAO phase have a wide spread in their correlations with observed precipitation, and their ensemble-mean precipitation correlation is close to zero. This suggests that the NAO phase had little effect on the CA winter precipitation patterns.

5. Conclusions

In 2016–2017, California experienced a reversal of the prolonged extreme drought conditions in 2011–2016 toward extreme wetness in 2016–2017 that had severe consequences on the state's infrastructure and resources (e.g., Seager et al., 2015; Swain et al., 2014; Wang et al., 2014; Wang, Yoon, et al., 2017). The strong 2015–2016 El Niño raised hopes of abundant rains to alleviate the drought but the winter season failed to ameliorate the drought in 2015–2016 (Steinschneider & Lall, 2016). This prompted several papers that assessed the robustness of the relationship between El Niño and California precipitation (Jong et al., 2016; Kumar & Chen, 2017; Lee et al., 2018; Paek et al., 2017) and examined the causes of poor rainfall predictions in the 2015–2016 seasonal forecasts (e.g., Cohen et al., 2017; Jong et al., 2018; Wanders et al., 2017; Wang, ameliorate, et al., 2017). The 2016–2017 winter season also posed a similar challenge as the forecasts were for a near-normal winter but ultimately ended up being one of the wettest winters on record (Wang, Anichowski, et al., 2017). Although precipitation was not well predicted, these seasons featured distinct large-scale midlatitude circulation anomalies over the North Pacific, which were generally well predicted. Examining the predictability of these circulation features and their association with California precipitation could inform model development efforts to improve seasonal predictions.

To evaluate the predictability of California precipitation and the associated atmospheric features in response to strong ocean forcing, we use 20-member, high-resolution GloSea5 forecast ensembles for these two winter seasons. The forecast spans the observed rainfall in Northern and Southern CA in 2015–2016, and in Southern CA in 2016–2017. Our analysis leads to three main findings. First, there was little skill in predicting the difference in precipitation for California despite the strong oceanic forcing differences between these seasons. The forecast difference in rainfall amounts for these seasons is significantly positive though substantially smaller than observed for Northern CA but indistinguishable for Southern CA. Second, there is high skill in ensemble mean predictions of the seasonal circulation patterns over the northern Pacific Ocean that influence the location of the storm tracks and therefore affect wintertime precipitation over California. The skill in predicting the upper-tropospheric circulation pattern is higher than the skill in predicting the lower-tropospheric pattern. Third, opposite forecasts of the high-latitude circulations relative to observed and, in particular, the AO, influenced the forecast precipitation differences across California. Though the AO was more positive in 2016–2017 than in 2015–2016, GloSea5 predicted anomalously negative AO conditions (Table 1).

Our analysis demonstrates that that an anomalously positive (negative) AO phase is associated with anomalously wetter (drier) conditions over California. While this result might appear to be at odds with other studies that show the opposite relationship (Fierro, 2014; Lim et al., 2018; McAfee & Russell, 2008; McCabe-Glynn et al., 2016), there are differences between these studies that could explain this conflict. A major difference between our study and earlier ones is that our study focuses on anomalies between these two specific seasons with contrasting tropical SST forcing, whereas other studies relate the general AO phase to seasonal (Fierro, 2014; McAfee & Russell, 2008) or extreme precipitation (McCabe-Glynn et al., 2016) anomalies over multiple seasons. Individual seasons can deviate from such general relationships due to interactions with other modes of natural atmospheric and oceanic variability (McCabe-Glynn et al., 2016). A systematic model-based investigation of the combined impacts of different phases of natural modes of variability on California seasonal precipitation to overcome the limitations of a short observational record could improve seasonal predictions.

Given that the large-scale, midlatitude circulation differences are predictable as a response to SST forcing, our findings suggest that internal atmospheric variability and its impact on precipitation over California were large enough in this case to preclude a skillful prediction. This supports several prior studies that suggest that internal variability was largely responsible for the inability of the seasonal forecasts to accurately predict the anomalous precipitation pattern in 2015–2016 despite the strong El Niño (Chen & Kumar, 2018; Jong et al., 2018; Lim et al., 2018; Wang, Anichowski, et al., 2017). However, we demonstrate that improved representation of processes affecting weather variability in the midlatitudes could facilitate improved precipitation predictions. One major source of variability in the midlatitudes is the AO (Higgins et al., 2000; Thompson & Wallace, 2000). Recent studies have demonstrated reasonably high skill in seasonal forecasts of the AO, including with GloSea5 (Kang et al., 2014; MacLachlan et al., 2015), which successfully predicted the SLP pattern for 2015–2016 (Scaife, Comer, Dunstone, Fereday, et al., 2017). However, while it was within the ensemble spread, the difference between the AO in winter 2016–2017 and 2015–2016 was not predicted by the ensemble mean, which likely affected the accuracy of the California winter rainfall forecast. Our results are supported by empirical forecasts (Wang, Ting, & Kushner, 2017), which indicate that statistically significant forecast skill of California precipitation can be gained through skillful predictions of the AO (their Figure 5). In addition, a recent study also highlights the propensity for extreme precipitation associated with atmospheric rivers during negative AO phases (McCabe-Glynn et al., 2016). Further improvements in the forecast skill of the AO could therefore improve seasonal and subseasonal predictions for California precipitation. In addition, improving our understanding of the mechanisms by which such high-latitude processes affect midlatitude weather and their representation in the forecast systems will also facilitate better predictions.

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References

Arribas, A., Glover, M., Maidens, A., Peterson, K., Gordon, M., MacLachlan, C., et al. (2010). The GloSea4 ensemble prediction system for seasonal forecasting. *Monthly Weather Review*, *139*(6), 1891–1910. https://doi.org/10.1175/2010MWR3615.1

Bjerknes, J. (1969). Atmospheric teleconnections from the equatorial Pacific. *Monthly Weather Review*, *97*(3), 163–172. https://doi.org/10.1175/1520-0493(1969)097<0163:ATFTEP>2.3.CO;2

Cayan, D. R., & Roads, J. O. (1984). Local relationships between United States west coast precipitation and monthly mean circulation parameters. *Monthly Weather Review*, *112*(6), 1276–1282. https://doi.org/10.1175/1520-0493(1984)112<1276:LRBUSW>2.0.CO;2

Chen, M., & Kumar, A. (2018). Winter 2015/16 atmospheric and precipitation anomalies over North America: El Niño response and the role of noise. *Monthly Weather Review*, *146*(3), 909–927. https://doi.org/10.1175/MWR-D-17-0116.1

Chen, M., Wei, S., Xie, P., Silva, V. B. S., Kousky, V. E., Higgins, R. W., & Janowiak, J. E. (2008). Assessing objective techniques for gauge-based analyses of global daily precipitation. *Journal of Geophysical Research*, *113*, D04110. https://doi.org/10.1029/2007JD009132

Chen, M., Xie, P., & Co-authors (2008). CPC Unified Gauge-based Analysis of Global Daily Precipiation, Western Pacific Geophysics Meeting, Cairns, Australia, 29 July - 1 August, 2008.

Cohen, J., Pfeiffer, K., & Francis, J. (2017). Winter 2015/16: A turning point in ENSO-based seasonal forecasts. *Oceanography*, *30*(1), 82–89. https://doi.org/10.5670/oceanog.2017.115

Dee, D. P., Uppala, S. M., Simmons, A. J., Berrisford, P., Poli, P., Kobayashi, S., et al. (2011). The ERA-Interim reanalysis: Configuration and performance of the data assimilation system. *Quarterly Journal of the Royal Meteorological Society*, *137*(656), 553–597. https://doi.org/10.1002/qj.828

Dettinger, M. D. (2013). Atmospheric Rivers as drought busters on the U.S. west coast. *Journal of Hydrometeorology*, *14*(6), 1721–1732. https://doi.org/10.1175/JHM-D-13-02.1

Fierro, A. O. (2014). Relationships between California rainfall variability and large-scale climate drivers. *International Journal of Climatology*, *34*(13), 3626–3640. https://doi.org/10.1002/joc.4112

Higgins, R. W., Leetmaa, A., Xue, Y., & Barnston, A. (2000). Dominant factors influencing the seasonal predictability of U.S. precipitation and surface air temperature. *Journal of Climate*, *13*(22), 3994–4017. https://doi.org/10.1175/1520-0442(2000)013<3994:DFITSP>2.0.CO;2

Hoell, A., Hoerling, M. P., Eischeid, J., Wolter, K., Randall, D., Perlwitz, J., et al. (2016). Does El Niño intensity matter for California precipitation? *Geophysical Research Letters*, *43*, 819–825. https://doi.org/10.1002/2015GL067102

Jong, B.-T., Ting, M., & Seager, R. (2016). El Niño's impact on California precipitation: Seasonality, regionality, and El Niño intensity. *Environmental Research Letters*, *11*(5), 54,021. https://doi.org/10.1088/1748-9326/11/5/054021

Jong, B. T., Ting, M., Seager, R., Henderson, N., & Lee, D. E. (2018). Role of equatorial Pacific SST forecast error in the late winter California precipitation forecast for the 2015/16 El Niño. *Journal of Climate*, *31*(2), 839–852. https://doi.org/10.1175/JCLI-D-17-0145.1

Kang, D., Lee, M.-I., Im, J., Kim, D., Kim, H.-M., Kang, H.-S., et al. (2014). Prediction of the Arctic Oscillation in boreal winter by dynamical seasonal forecasting systems. *Geophysical Research Letters*, *41*, 3577–3585. https://doi.org/10.1002/2014GL060011

Kumar, A., & Chen, M. (2017). What is the variability in US west coast winter precipitation during strong El Niño events? *Climate Dynamics*, *49*(7–8), 2789–2802. https://doi.org/10.1007/s00382-016-3485-9

Lee, S.-K., Lopez, H., Chung, E.-S., DiNezio, P., Yeh, S.-W., & Wittenberg, A. T. (2018). On the fragile relationship between El Niño and California rainfall. *Geophysical Research Letters*, *45*, 907–915. https://doi.org/10.1002/2017GL076197

L'Heureux, M. L., Takahashi, K., Watkins, A. B., Barnston, A. G., Becker, E. J., di Liberto, T. E., et al. (2016). Observing and predicting the 2015/16 El Niño. *Bulletin of the American Meteorological Society*, *98*(7), 1363–1382. https://doi.org/10.1175/BAMS-D-16-0009.1

Lim, Y.-K., Schubert, S. D., Chang, Y., Molod, A. M., & Pawson, S. (2018). The impact of SST-forced and unforced teleconnections on 2015/16 El Niño winter precipitation over the western United States. *Journal of Climate*, *31*(15), 5825–5844. https://doi.org/10.1175/JCLI-D-17-0218.1

MacLachlan, C., Arribas, A., Peterson, K. A., Maidens, A., Fereday, D., Scaife, A. A., et al. (2015). Global Seasonal Forecast System version 5 (GloSea5): A high-resolution seasonal forecast system. *Quarterly Journal of the Royal Meteorological Society*, *141*(689), 1072–1084. https://doi.org/10.1002/qj.2396

McAfee, S. A., & Russell, J. L. (2008). Northern annular mode impact on spring climate in the western United States. *Geophysical Research Letters*, *35*, L17701. https://doi.org/10.1029/2008GL034828

McCabe-Glynn, S., Johnson, K. R., Strong, C., Zou, Y., Yu, J. Y., Sellars, S., & Welker, J. M. (2016). Isotopic signature of extreme precipitation events in the western U.S. and associated phases of Arctic and tropical climate modes. *Journal of Geophysical Research: Atmospheres*, *121*, 8913–8924. https://doi.org/10.1002/2016JD025524

Paek, H., Yu, J. Y., & Qian, C. (2017). Why were the 2015/2016 and 1997/1998 extreme El Niños different? *Geophysical Research Letters*, *44*, 1848–1856. https://doi.org/10.1002/2016GL071515

Scaife, A. A., Arribas, A., Blockley, E., Brookshaw, A., Clark, R. T., Dunstone, N., et al. (2014). Skillful long range prediction of European and North American winters. *Geophysical Research Letters*, *41*, 2514–2519. https://doi.org/10.1002/2014GL059637

Scaife, A. A., Comer, R., Dunstone, N., Fereday, D., Folland, C., Good, E., et al. (2017). Predictability of European winter 2015/2016. *Atmospheric Science Letters*, *18*(2), 38–44. https://doi.org/10.1002/asl.721

Scaife, A. A., Comer, R. E., Dunstone, N. J., Knight, J. R., Smith, D. M., MacLachlan, C., et al. (2017). Tropical rainfall, Rossby waves and regional winter climate predictions. *Quarterly Journal of the Royal Meteorological Society*, *143*(702), 1–11. https://doi.org/10.1002/qj.2910

Seager, R., Hoerling, M., Schubert, S., Wang, H., Lyon, B., Kumar, A., et al. (2015). Causes of the 2011–14 California drought. *Journal of Climate*, *28*(18), 6997–7024. https://doi.org/10.1175/JCLI-D-14-00860.1

Seager, R., Naik, N., Ting, M., Cane, M. A., Harnik, N., & Kushnir, Y. (2010). Adjustment of the atmospheric circulation to tropical pacific SST anomalies: Variability of transient eddy propagation in the Pacific-North America sector. *Quarterly Journal of the Royal Meteorological Society*, *136*(647), n/a–296. https://doi.org/10.1002/qj.588

Smith, A., Lott, N., Houston, T., Shein, K., Crouch, J., & Enloe, J. (2018). U.S. billion-dollar weather and climate disasters 1980–2018.

Steinschneider, S., & Lall, U. (2016). El Niño and the U.S. precipitation and floods: What was expected for the January–March 2016 winter hydroclimate that is now unfolding? *Water Resources Research*, *52*, 1498–1501. https://doi.org/10.1002/2015WR018470

Swain, D. L., Horton, D. E., Singh, D., & Diffenbaugh, N. S. (2016). Trends in atmospheric patterns conducive to seasonal precipitation and temperature extremes in California seasonal precipitation and temperature extremes. *Science Advances*, *2*(4), e1501344. https://doi.org/10.1126/sciadv.1501344

Swain, D. L., Tsiang, M., Haugen, M., Singh, D., Charland, A., Rajaratnam, B., & Diffenbaugh, N. S. (2014). The extraordinary California drought of 2013/2014: Character, context, and the role of climate change. *Bulletin of the American Meteorological Society*, *95*(9).

Thompson, D. W. J., & Wallace, J. M. (2000). Annular modes in the extratropical circulation. Part II: Trends. *Journal of Climate*, *13*(5), 1018–1036. https://doi.org/10.1175/1520-0442(2000)013<1018:AMITEC>2.0.CO;2

Trenberth, K. E., Branstator, G. W., Karoly, D., Kumar, A., Lau, N.-C., & Ropelewski, C. (1998). Progress during TOGA in understanding and modeling global teleconnections associated with tropical sea surface temperatures. *Journal of Geophysical Research*, *103*(C7), 14,291–14,324. https://doi.org/10.1029/97JC01444

Wanders, N., Bachas, A., He, X. G., Huang, H., Koppa, A., Mekonnen, Z. T., et al. (2017). Forecasting the hydroclimatic signature of the 2015/16 El Niño event on the Western United States. *Journal of Hydrometeorology*, *18*(1), 177–186. https://doi.org/10.1175/JHM-D-16-0230.1

Wang, L., Ting, M., & Kushner, P. J. (2017). A robust empirical seasonal prediction of winter NAO and surface climate. *Scientific Reports*, *7*(1), 279. https://doi.org/10.1038/s41598-017-00353-y

Wang, S., Anichowski, A., Tippett, M. K., & Sobel, A. H. (2017). Seasonal noise versus subseasonal signal: Forecasts of California precipitation during the unusual winters of 2015–2016 and 2016–2017. *Geophysical Research Letters*, *44*, 9513–9520. https://doi.org/10.1002/2017GL075052

Wang, S. -Y., Hipps, L., Gillies, R. R., & Yoon, J.-H. (2014). Probable causes of the abnormal ridge accompanying the 2013–2014 California drought: ENSO precursor and anthropogenic warming footprint. *Geophysical Research Letters*, *41*, 3220–3226. https://doi.org/10.1002/2014GL059748

Wang, S.-Y. S., Yoon, J.-H., Becker, E., & Gillies, R. (2017). California from drought to deluge. *Nature Climate Change*, *7*(7), 465–468. https://doi.org/10.1038/nclimate3330

Xie, P., Chen, M., Yang, S., Yatagai, A., Hayasaka, T., Fukushima, Y., & Liu, C. (2007). A gauge-based analysis of daily precipitation over East Asia. *Journal of Hydrometeorology*, *8*(3), 607–626. https://doi.org/10.1175/JHM583.1