California Winter Precipitation Predictability: Insights from the anomalous 2015-16 and 2016-17 seasons

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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 (200mb) circulation anomalies relative to the lower-level (850mb) 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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Abstract (150 words)

The unexpected dry 2015-16 El Niño winter and extremely wet 2016-17 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 mid-latitude 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 were not well predicted in the ensemble-mean for these seasons. Improved representation of high-latitude processes such as the AO 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 2015-16 El Niño that typically brings heavy rains, California unexpectedly experienced one of its wettest winter seasons on record during the 2016-17 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 extra-tropical 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 mid-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 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 2015-16 and 2016-17 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 [*Steinschneider and Lall*, 2016; *Cohen et al.*, 2017; *Chen and Kumar*, 2018] and to ameliorate the prolonged 2012-2016 drought [*Swain et al.*, 2014; *Wang et al.*, 2014; *Seager et al.*, 2015], the winter season was close to normal for Northern California and below normal for Southern California [*Jong et al.*, 2018]. In contrast, 2016-17 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 2016-17 season [*Wang et al.*, 2017b]. 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 2015-16 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; *Wanders et al.*, 2017; *Lee et al.*, 2018]). 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. [*Kumar and Chen*, 2017; *Chen and Kumar*, 2018; *Jong et al.*, 2018]). In the 2015-16 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 [*Wang et al.*, 2017c; *Chen and Kumar*, 2018; *Jong et al.*, 2018]. In addition, while the difficulty of ensemble forecasts to predict the extreme wetness in parts of California in 2016-17 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 mid-latitude blocking [*Wanders et al.*, 2017] that are relevant for precipitation over this region.

California receives the bulk of its precipitation from short-lived mid-latitude 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 and Roads*, 1984; *Wang et al.*, 2014; *Seager et al.*, 2015; *Swain et al.*, 2016]. These anomalous seasons of 2015-16 and 2016-17 that had large differences in circulation patterns and seasonal precipitation provide a testbed 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 2015-16 and 2016-17 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 (CPC) Global Unified Gauge-Based Analysis of Daily Precipitation data at a spatial resolution of 0.5°x0.5° [*Xie et al.*, 2007; *Chen et al.*, 2008a, 2008b]. Monthly geopotential heights (GPH) and sea-level pressures (SLP) are from the ERA-Interim Reanalysis dataset by the European Center for Medium-Range Weather Forecasting (ECMWF) [*Dee et al.*, 2011].

To examine the differences in winter (DJF) precipitation and circulation patterns, we analyze the 20-member forecast ensembles for 2015-16 and 2016-17 winter seasons from the UK Met Office Global Seasonal Forecast System version 5 (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 process affecting the mid-latitudes and provides high prediction skill for natural modes of variability such as El Niño-Southern Oscillation, North Atlantic Oscillation, and the Arctic Oscillation [*Scaife et al.*, 2014; *MacLachlan et al.*, 2015]. The ensemble members of the winter forecasts are initialized on 10 dates centered around November 1st. 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 2015-16 El Niño and the Atlantic circulation anomaly [*Scaife et al.*, 2017a], 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 ensemble of potential differences between 2016-17 and 2015-16 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 2016-17, the average winter rainfall across northern and southern California was heavier than in 2015-16 (Fig. 1a-c). GloSea5 ensemble mean forecasts simulate slightly wetter conditions over northern California in 2016-17 than 2015-16, but the simulated mean differences between the two seasons were ~ 12% of the magnitude of the observed differences (Fig. 1d-f). 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 2016-17 relative to 2015-16 although with lower magnitude than observed (Fig. 1g-i). In contrast, the median difference in forecasts for southern California is indistinguishable from zero while rainfall was overestimated in 2015-16 and underestimated in 2016-17 (Fig. 1g-i). Despite the expectation of a stronger influence of El Niño on southern California relative to northern California [*Jong et al.*, 2016], the strong 2015-16 El Niño did not result in forecasts of substantially higher rainfall over the region relative to 2016-17. While the differences between 2015-16 and 2016-17 winter seasons for northern and southern California are within the range of the forecasts (Fig. 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 (Fig. 2). At the upper level (200mb), there was anomalously high GPH in the northern-central Pacific and anomalously low GPH across much of the tropical and subtropical Pacific in 2016-17 relative to the 2015-16 winter. This dipole pattern resulted from the anomalous high-pressure over the North Pacific in response to the weak La Niña in 2016-17 and the deepening of the Aleutian Low and warming of the tropical atmosphere in response to the El Niño in 2015-16 (e.g. [*Bjerknes*, 1969; *Trenberth et al.*, 1998; *Seager et al.*, 2010]). This GPH pattern indicates a relatively northward shifted position of the Pacific storm track in 2016-17 relative to 2015-16. In addition, the opposite GPH dipole over North America guided the storm tracks towards California in 2016-17 relative to the previous winter. GloSea5 accurately captured the overall trough-ridge-trough-ridge over the North Pacific and western North America. In particular, the spatial correlation between the ensemble mean forecast and the observed differences between 2016-17 relative to 2015-16 over the Pacific (Fig. 2a) was 0.89 (Fig. 2b). The forecast ensemble spread in the correlations with the observed differences largely exceeded 0.5 (Fig. 3a).

In the lower-troposphere (850mb), GPH anomalies are largest in the mid-latitudes with an anomalous low-high pattern across the Pacific in the 2016-17 season relative to 2015-16 (Fig. 2c-d). 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 (Fig. 2d), albeit with a relatively larger spread in correlations within the ensemble than for the 200mb correlations (Fig. 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 et al.*, 2017b]). Despite the high correlations in the ensemble means of the 200mb and 850mb 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 (Fig. 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 850mb GPH anomalies over the western United States 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 highest ("successful") and lowest ("unsuccessful") 5th percentiles of the distribution (Fig. 4a-b). The "successful" subset of ensemble members reproduces the magnitude and spatial pattern of precipitation differences between winter 2015-16 and 2016-17 and have correlations with observations exceeding 0.8 (Fig. 1c, 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 mid and high-latitudes between these ensemble subsets that explain these contrasts in precipitation patterns (Fig. 4c-f). 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 (Fig. 4c,e). This configuration represents a weakening of the climatological ridge over the northeast Pacific and directs the storm tracks towards California, consistent with the composite precipitation pattern that shows widespread wetness across California (Fig. 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 (Fig. 4b,d,f). 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 (Fig. 2a,c), the pattern of GPH anomalies in the composite of the “successful” subset indicates a stronger polar vortex in 2016-17 relative to 2015-16 representing a more positive Arctic Oscillation (AO) phase (Fig. 4c,e), whereas the pattern of GPH anomalies in the composite of the “unsuccessful” subset represents a more negative AO phase (Fig. 4d,f).

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 (Fig. 3b). To do so, we define the AO index as the area-weighted mean SLP differences between 35-55ºN and 60-90ºN, 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 (Fig. 3b). A majority of ensemble members with positive AO phases in 2016-17 relative to 2015-16 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 (Fig. 3a-b). With a few exceptions, the entire distribution of model and observed precipitation correlations for ensemble members with positive AO phases is positive and 95 percent 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 2016-17 relative to 2015-16. 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 (Fig. 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 North Atlantic Oscillation (NAO) phase (Fig. 3c) suggests a relatively weaker and more uncertain effect on these seasonal California precipitation differences. The NAO was anomalously negative in 2016-17 relative to 2015-16, 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 2016-17, California experienced a reversal of the prolonged extreme drought conditions in 2011-2016 towards extreme wetness in 2016-17 that had severe consequences on the state's infrastructure and resources (e.g. [*Swain et al.*, 2014; *Wang et al.*, 2014, 2017b; *Seager et al.*, 2015]). The strong 2015-16 El Niño raised hopes of abundant rains to alleviate the drought but the winter season failed to alleviate the drought in 2015-16 [*Steinschneider and Lall*, 2016]. This prompted several papers that assessed the robustness of the relationship between El Niño and California precipitation [*Jong et al.*, 2016; *Kumar and Chen*, 2017; *Paek et al.*, 2017; *Lee et al.*, 2018] and examined the causes of poor rainfall predictions in the 2015-16 seasonal forecasts (e.g.[*Cohen et al.*, 2017; *Wanders et al.*, 2017; *Wang et al.*, 2017c; *Jong et al.*, 2018]). The 2016-17 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 et al.*, 2017c]. Although precipitation was not well predicted, these seasons featured distinct large-scale mid-latitude 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 2015-16, and in Southern CA in 2016-17. 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

Arctic Oscillation, influenced the forecast precipitation differences across California. Though the AO was more positive in 2016-17 than in 2015-16, 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 [*McAfee and Russell*, 2008; *Fierro*, 2014; *McCabe-Glynn et al.*, 2016; *Lim et al.*, 2018], 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 [*McAfee and Russell*, 2008; *Fierro*, 2014] 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, mid-latitude circulation differences are predictable as a response to SST forcing, our findings suggest that internal atmospheric variability and its impact on precipitation over California was 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 2015-16 despite the strong El Niño [*Wang et al.*, 2017c; *Chen and*

Kumar, 2018; *Jong et al.*, 2018; *Lim et al.*, 2018]. However, we demonstrate that improved representation of processes affecting weather variability in the mid-latitudes could facilitate improved precipitation predictions. One major source of variability in the mid-latitudes is the Arctic Oscillation [*Higgins et al.*, 2000; *Thompson and 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 sea-level pressure pattern for 2015-16 [*Scaife et al.*, 2017a]. However, while it was within the ensemble spread, the difference between the AO in winter 2016-17 and 2015-16 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 et al.*, 2017a] which indicate that statistically significant forecast skill of California precipitation can be gained through skillful predictions of the AO (their Fig. 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 mid-latitude weather and their representation in the forecast systems will also facilitate better predictions.

Acknowledgments and Data Access

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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. (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.

		2015-16	**2016-17**	**Difference**
(a) AO Index	**ERA-Interim**	458.6	716.9	258.3
	GloSea5	386.7	238.5	-148.2
(b) NAO Index	**ERA-Interim**	1749.6	1369.2	-380.4
	GloSea5	1632.5	1196.4	-436.1

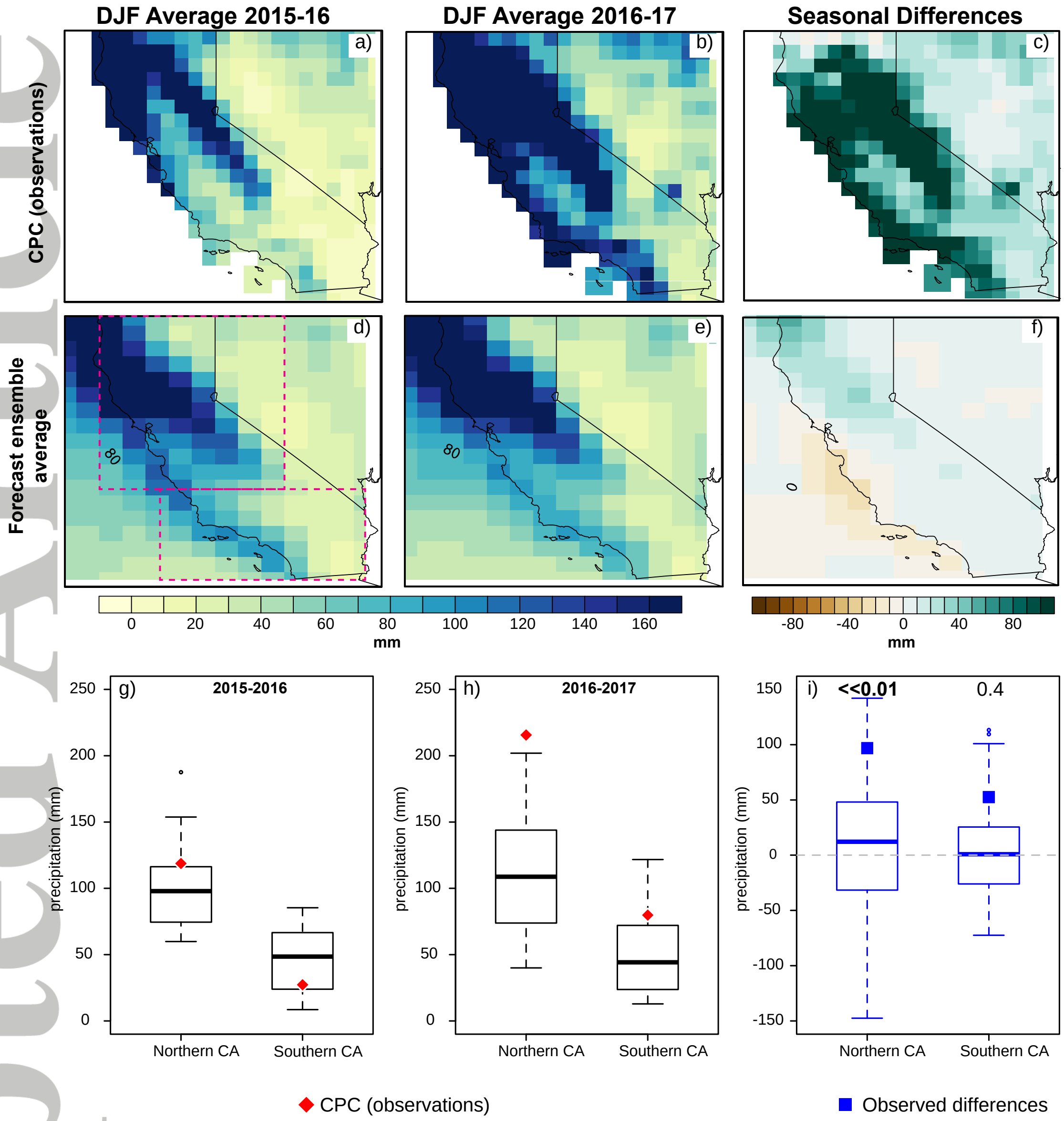

Figure 1. Observed and simulated precipitation: California winter season (DJF) average rainfall for 2015-16 and 2016-17 from the (a-b) NOAA Climate Prediction Center (CPC) observations and (d-e) UK Met Office seasonal forecast systems ensemble. (c) Observed and (f) forecast differences in rainfall between 2016-17 and 2015-16 seasonal averages. Boxplots show the area-average seasonal (g-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, whiskers represent the 5th/95th percentile and dots represent outliers of the distribution.

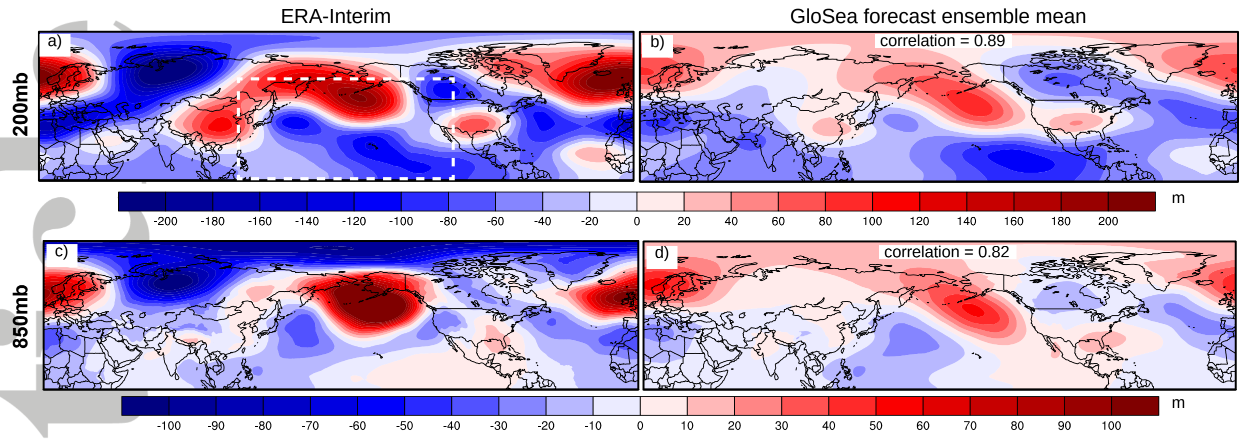

Figure 2. **Observed and simulated circulation patterns:** Difference in (a-b) 200mb and (c-d) 850mb seasonal (DJF) mean geopotential heights between 2016-17 and 2015-16 in ERA-Interim Reanalysis and the GloSea forecast ensemble. Correlations in panel (b,d) refer to the spatial correlation in geopotential height differences in ERA-Interim and the forecast ensemble mean over the Pacific basin (grey box in panel (a)).

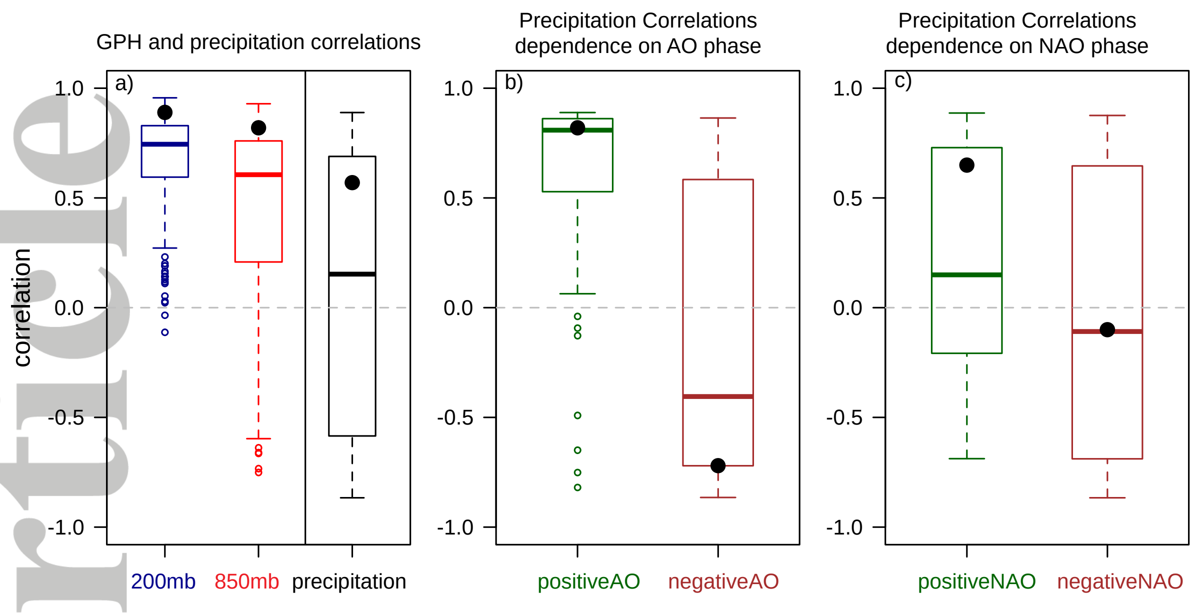

Figure 3. Relationship between circulation patterns and precipitation: Boxplots showing the distribution of correlations between model forecast and observed differences between 2016-17 and 2015-16 in (a) 200mb and 850 mb geopotential heights (GPH) over the Pacific domain (shown in Fig. 2a) and precipitation over California. In the boxplots, 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 CPC data. Heavy dots are the spatial correlations between the GloSea5 ensemble mean of each variable with the corresponding observations. (b-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. Black dots in panels (b-c) are correlations of the ensemble mean precipitation patterns of the respective subsets with the observed precipitation.

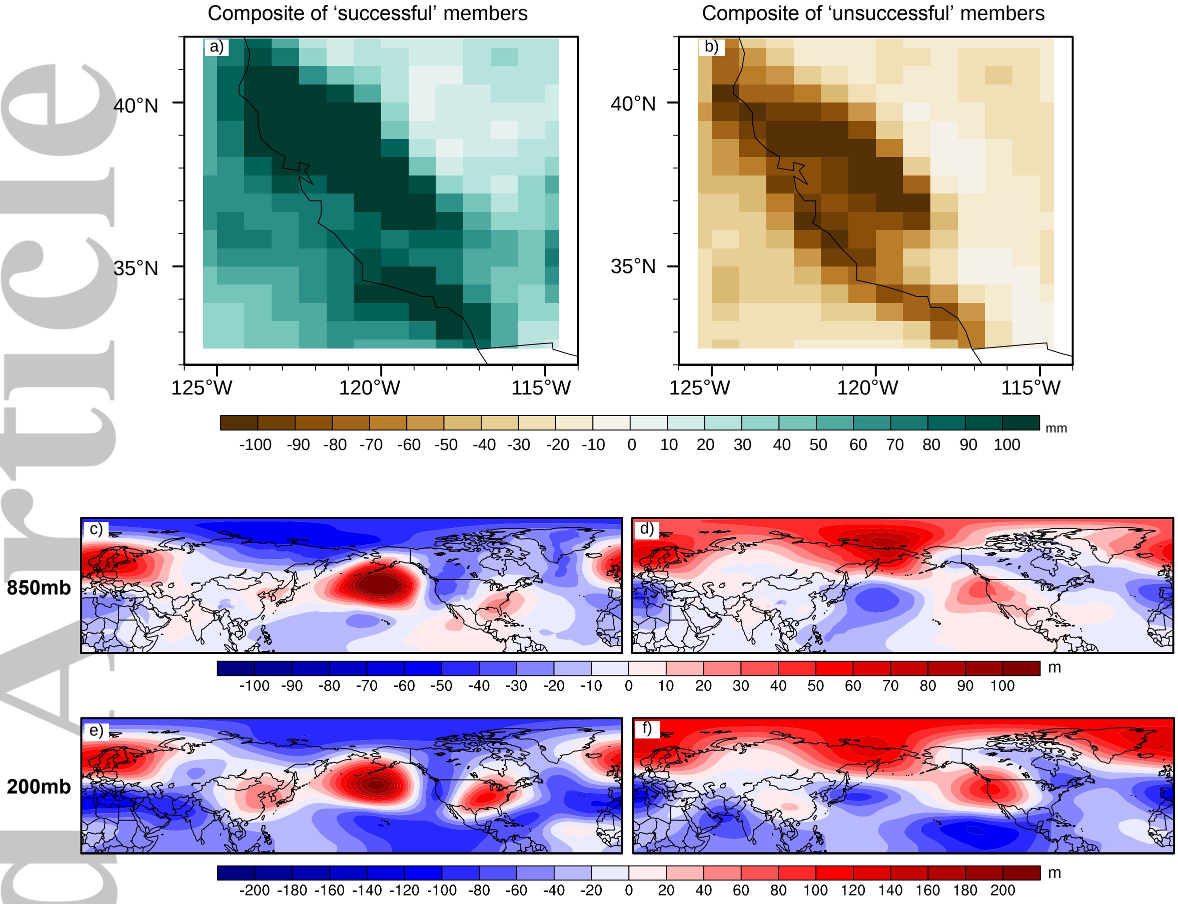

Figure 4. Successful and unsuccessful forecasts: Composite differences between the 2015-16 and 2016-17 winter season (a-b) precipitation, (c-d) 850mb geopotential heights, and (e-f) 200mb geopotential heights for the 5th percentile of ensemble members with the highest (left) and lowest (right) correlations with observed (CPC) precipitation differences.