ABSTRACT

The major El Niño of 2015/16 brought significantly less precipitation to California than previous events of comparable strength, much to the disappointment of residents suffering through the state’s fourth consecutive year of severe drought. Here, California’s weak precipitation in 2015/16 relative to previous major El Niño events is investigated within a 40-member ensemble of atmosphere-only simulations run with historical sea surface temperatures (SSTs) and constant radiative forcing. The simulations reveal significant differences in both California precipitation and the large-scale atmospheric circulation between 2015/16 and previous strong El Niño events, which are similar to (albeit weaker than) the differences found in observations. Principal component analysis indicates that these ensemble-mean differences were likely related to a pattern of tropical SST variability with a strong signal in the Indian Ocean and western Pacific and a weaker signal in the eastern equatorial Pacific and subtropical North Atlantic. This SST pattern was missed by the majority of forecast models, which could partly explain their erroneous predictions of above-average precipitation in California in 2015/16.

1. Introduction

Before 2015/16, the strongest El Niños on record occurred in 1982/83 and 1997/98—the only previous winters in which sea surface temperature (SST) anomalies in the Niño-3.4 region have exceeded 2°C (Fig. 1a). Driven by an eastward shift in tropical Pacific convection, each of these winters saw a deepening of the Aleutian low over the northeastern Pacific, resulting in intense storms and copious precipitation over much of the southwestern United States (Figs. 2b,d). In California, in particular, precipitation during the winters of 1982/83 and 1997/98 exceeded 150% of average over much of the state, filling reservoirs but also causing extensive flooding and landslides (Storlazzi et al. 2000; Changnon 1999).

In a recent study of atmospheric model simulations forced by historical SSTs, Hoell et al. (2016) found that such extreme precipitation is typical of strong El Niños and that the likelihood of below-average precipitation in California during such events is quite low, especially in the southern part of the state (around 10%). Understandably, therefore, many hoped that the El Niño of 2015/16—which models correctly predicted would match the strength of the 1982/83 and 1997/98 events (Fig. 1)—would bring a resounding end to the severe drought that had afflicted California since 2012 (Swain et al. 2014). This hope was bolstered by seasonal forecast models, which even in November were still predicting wintertime precipitation anomalies similar to those of previous strong El Niños (Figs. 2a,c,e). In reality,
however, the storm track largely avoided California in 2015/16, leaving much of the state unusually dry even by the standards of a normal winter, but especially compared with previous strong El Niños (Fig. 2c; Kintisch 2016).

At least two factors could have contributed to California’s lack of precipitation in 2015/16 relative to 1982/83 and 1997/98. First, despite similar magnitudes of warm SST anomalies in the canonical Niño-3.4 region during all three winters, significant differences were present in other regions (Figs. 1b–d), which could have modulated the atmospheric response in ways that led to a lower likelihood of wet conditions in 2015/16. On the other hand, even if the likelihood of wet conditions had been identical during all three events, precipitation differences could still have arisen from internal variability (i.e., chaos) in the atmospheric circulation, which is independent of SST influence (Hoerling and Kumar 1997; Kumar and Hoerling 1997). Here we show that both factors likely played a role in differentiating 2015/16 from previous strong El Niños and that SST biases in seasonal forecasts may have contributed to their erroneous prediction of a wetter-than-average winter in California in 2015/16.

2. Data and methods

We performed 40 simulations of the historical climate from 1950–2016 using the Geophysical Fluid Dynamics Laboratory (GFDL) Atmospheric Model, version 2.1 (AM2.1), at a resolution of 2° latitude £ 2.5° longitude, with constant radiative forcing (set to 1990 levels) and historical SSTs taken from the NOAA Extended Reconstruction SST dataset (version 3b). Each ensemble member was started in 1949 with slightly different initial conditions, such that the ensemble spread can be interpreted as a proxy for internal atmospheric variability. We additionally performed a few sets of sensitivity experiments with perturbed SSTs, also with 40 ensemble members (details of these experiments are given later). Grid points with SST less than £1.8°C are regarded as 100% sea ice fraction. Further details about the model configuration can be found in Johnson and Kosaka (2016). Our analysis focuses on interannual variability in the wintertime mean, defined here as December–February. However, our results do not significantly depend on this definition, as we confirmed by repeating the analysis using wintertime means from November–March (not shown).

The observational estimates used in our analysis include the monthly ERA-Interim product (for geopotential height; Dee et al. 2011), the Climate Prediction Center’s (CPC) Merged Analysis of Precipitation (CMAP; Xie and Arkin 1997), and the 4-km gridded monthly precipitation product from the PRISM Climate Group at Oregon State University (for precipitation over the continental United States; Daly et al. 1994). Forecast model output was taken from the North American Multimodel Ensemble (NMME) archive hosted by the International Research Institute for Climate and...
FIG. 2. (a) The ensemble-mean precipitation forecast for the winter of 1982/83 (November–March) in the western United States, expressed as a percentage of the 1982–2016 average. The forecasts were taken from the NMME and were generated by six different models: COLA-RSMAS-CCSM3 (6 members), COLA-RSMAS-CCSM4 (10 members), GFDL-CM2p1-aero (10 members), GFDL-CM2p5-FLOR-A06 (12 members), GFDL-CM2p5-FLOR-B01 (12 members), and NASA-GMAO-062012 (11 members). (b) The observed precipitation anomaly over the same period of 1982/83, from PRISM (over the continental United States) and CMAP (elsewhere). (c),(d) As in (a),(b), but for the winter of 1997/98. (e),(f) As in (a),(b), but for the winter of 2015/16.
Society at Columbia University (Kirtman et al. 2014; http://iridl.ldeo.columbia.edu/SOURCES/.Models/.NMME/). We focus exclusively on forecasts initialized in November 2015 for the following December–February and consider only those NMME models (listed in the caption of Fig. 2) for which hindcasts of SST and precipitation date back to 1982. In contrast to our GFDL AM2.1 simulations, in which only the atmosphere and land surface are permitted to evolve, the NMME forecasts are more comprehensive, most notably because they are coupled to a dynamical ocean model. All anomalies (in models and observations) were calculated relative to the same baseline climatology from 1982/83 through 2015/16. For the forecast models, unique climatologies were defined for each model as the average winter forecast over all years and ensemble members with November initializations.

3. Results

Figure 3a shows the amount of precipitation in Northern (Figs. 3a–c) and Southern (Figs. 3d–f) California, simulated by the GFDL AM2.1 during the winters of 1982/83, 1997/98, and 2015/16. Precipitation is expressed as the average percent departure from climatology over all grid points within the stated regions, which are defined relative to the 38th parallel. Looking at the distributions of precipitation across the ensemble (gray histograms), we find that the ensemble spread is quite large in all cases, indicating the strong influence of internal atmospheric variability on wintertime precipitation across the state. The upper tails of the distributions are particularly large in the south in 1982/83 and 1997/98, with precipitation exceeding 300% of climatology in some ensemble members. Yet when we compare the ensemble means (blue diamonds), we find that internal variability likely does not explain all of the observed differences between 2015/16 and previous events.

In the south, for example, 2015/16 is significantly drier in the ensemble mean than both 1982/83 and 1997/98, by 52% and 38% of climatology, respectively. These differences in ensemble-mean precipitation cannot explain all of the differences in observed precipitation between 2015/16 and previous El Niños, which amounted to 88% and 140% of climatology, respectively (red diamonds). Indeed, whereas observed precipitation was a bit below the ensemble-mean value in 2015/16, it was above the ensemble-mean value in 1982/83 and 1997/98, suggesting that internal atmospheric variability likely played a significant role. The relative contributions of internal versus SST-driven variability are easily estimated if one assumes that the ensemble distributions are roughly normal and that the ensemble-mean differences are representative of the SST contribution (see appendix A). Given these assumptions, we estimate that, of the observed differences in Southern California precipitation between 2015/16 and 1982/83 (1997/98), 59% ± 27% (27% ± 16%) can be attributed to SST differences and the remainder to internal atmospheric variability (90% confidence).
In the north, the distributions are considerably narrower than in the south during all three El Niño winters. As in the south, however, the ensemble-mean precipitation is significantly lower in 2015/16 than in 1997/98; 2015/16 is also a bit drier than 1982/83, although the difference is not statistically significant. Based on the same assumptions described in the preceding paragraph, we estimate that SSTs were responsible for 46% ± 57% of the difference in Northern California precipitation between 2015/16 and 1982/83, and 68% ± 31% of the difference between 2015/16 and 1997/98. This suggests that SST differences in 2015/16 very likely contributed to the drier conditions in Northern California relative to 1997/98 but played less of a role relative to 1982/83.

To gain insight into the dynamical causes of differences in California precipitation, Fig. 4 shows the difference in 200-hPa geopotential heights $Z_{200}$ between 2015/16 and the previous two El Niños, in observations (Figs. 4a,b) and in the ensemble mean (Figs. 4c,d). Compared with both previous strong El Niños, 2015/16 exhibited higher $Z_{200}$ over much of the lower mid-latitudes of the Northern Hemisphere in observations (Figs. 4a,b). From geostrophic balance, this pattern implies a poleward shift of the subtropical jet and was therefore accompanied by a reduction in precipitation not just in California, but over much of the entire latitude band between 20° and 40°N (not shown). Comparing the observed differences in $Z_{200}$ with the ensemble mean of the simulations (Figs. 4c,d), we find a broadly similar pattern, albeit weaker in most places. This result is consistent with our earlier analysis of California precipitation (Fig. 3), which suggested that SST differences likely contributed to—but cannot entirely explain—the observed differences between 2015/16 and previous strong El Niños.

Together, Figs. 3a and 4 provide strong evidence that the differences in California precipitation between 2015/16 and previous strong El Niños were caused in part by SST differences outside the Niño-3.4 region (Fig. 1a). To find out which regions may have played the greatest role, it is instructive to identify the leading modes of variability in deep tropical convection [as indicated by outgoing longwave radiation (OLR)], which is closely tied to variability in both tropical SSTs and the extratropical atmospheric circulation (e.g., Hoskins and Karoly 1981; Kiladis and Weickmann 1992).

Figure 5 shows the three leading principal components (PCs) of simulated tropical wintertime OLR over the Indian and Pacific Oceans as a function of time (Figs. 5a–c), along with their corresponding empirical orthogonal functions (EOFs; Figs. 5d–f) and maps of their correlation with SST (Figs. 5g–i), $Z_{200}$ (Figs. 5j,k), and precipitation (Figs. 5m–o). The decomposition was performed over all 66 years of the simulation period and all ensemble members and therefore incorporates 2640 distinct winter seasons. To mute the influence of global
warming on SST and $Z_{200}$, the correlations in Figs. 5g–l were calculated after first subtracting the average value of each field over the domains shown \(^1\) (see Fig. 5 caption for details). In Figs. 5a–c, the blue lines represent the average value of each PC across all ensemble members, with gray shading indicating the full range of PC values across the ensemble. The red lines represent the observed PC, found by projecting OLR from reanalysis onto its respective EOF. The gray shading encompasses the full range of PC values across the ensemble. Green lines indicate strong El Niño winters. (d)–(f) The three leading EOFs, represented here as the correlation between each PC and OLR at each grid point. The green box outlines the domain over which the EOF decomposition was performed (between 10°S and 10°N). (g)–(i) The correlation between the ensemble mean of each PC and SST* at each grid point. Statistically significant correlations are indicated by stippling, based on the false discovery rate (FDR) method described by Wilks (2016). (j)–(l) The correlation between the ensemble mean of each PC and the ensemble-mean of $Z_{200}^*$ at each grid point, with $Z_{200}^*$ defined as the local $Z_{200}$ departure from the global mean. (m)–(o) The correlation between the ensemble mean of each PC and the ensemble mean of precipitation at each grid point. [The green line in (i) encloses the IWP region, for the purposes of the SST perturbation experiments presented in Figs. 6 and 7.]

\(^1\) Following Chen and Wallace (2015), we refer to the adjusted fields as SST* and $Z_{200}^*$. 

Fig. 5. PC analysis of wintertime OLR in the deep tropics of the Indian and Pacific Oceans, performed over all years and all ensemble members. (a)–(c) The ensemble-mean value of each of the three leading PCs (solid blue lines) and their long-term trends (dashed blue lines). The red line represents the observed PC, found by projecting OLR from reanalysis onto its respective EOF. The gray shading encompasses the full range of PC values across the ensemble. Green lines indicate strong El Niño winters. (d)–(f) The three leading EOFs, represented here as the correlation between each PC and OLR at each grid point. The green box outlines the domain over which the EOF decomposition was performed (between 10°S and 10°N). (g)–(i) The correlation between the ensemble mean of each PC and SST* at each grid point. Statistically significant correlations are indicated by stippling, based on the false discovery rate (FDR) method described by Wilks (2016). (j)–(l) The correlation between the ensemble mean of each PC and the ensemble-mean of $Z_{200}^*$ at each grid point, with $Z_{200}^*$ defined as the local $Z_{200}$ departure from the global mean. (m)–(o) The correlation between the ensemble mean of each PC and the ensemble mean of precipitation at each grid point. [The green line in (i) encloses the IWP region, for the purposes of the SST perturbation experiments presented in Figs. 6 and 7.]
variability in tropical convection in the Pacific and Indian Oceans.

Let us examine each PC in turn, beginning with the first. PC1 accounts for 42% of the total variance in OLR, and its variability closely tracks the Niño-3.4 index ($r = 0.96$). Not surprisingly, therefore, its corresponding EOF is indistinguishable from the canonical El Niño response, characterized by an eastward shift in tropical convection toward the central and eastern Pacific and away from the climatological warm pool in the western Pacific (Fig. 5d). The correlation maps likewise reflect well-known El Niño impacts, including a stronger Aleutian low (Fig. 5j) (Horel and Wallace 1981; Wallace et al. 1998) and positive precipitation anomalies over much of the southern United States, including California. To further evaluate the relationship between PC1 and California precipitation, Table 1 gives the correlation coefficient between the ensemble mean of PC1 and ensemble-mean precipitation in Northern California (top row), Southern California (middle row), and the entire state (bottom row). While the correlation is close to zero in the north ($r = -0.05$), it is significant in the south ($r = 0.46$) and in the state overall ($r = 0.37$). These correlations are similar to those found in observations. PC1 strongly positive during all three major El Niños (1.91$\sigma$, 2.09$\sigma$, and 2.10$\sigma$), and thus accounts for little of the precipitation or circulation differences evident in Figs. 3 and 4.

The second PC is also associated with tropical Pacific variability (Fig. 5e), but in contrast to PC1, it is driven primarily by an SST tripole in the west–central–east Pacific (Fig. 5h), similar to the so-called Modoki mode of Pacific SST variability described by Ashok et al. (2007) and Weng et al. (2007). PC2 has a widespread impact on the atmospheric circulation over North America (Fig. 5k), displacing the Pacific–North American pattern associated with PC1 eastward (Yu et al. 2012; Chiodi and Harrison 2013). Indeed, Paek et al. (2017) showed that during the decay phase of El Niño (March–May), cooler (warmer) temperatures in the eastern (central) Pacific shifted the Northern Hemisphere teleconnection pattern westward in 2016 relative to 1998, helping to reduce precipitation in California. In winter, however, PC2 has no impact on precipitation in Southern California, where the contrast among the El Niños was greatest ($r = -0.08$; Table 1). Moreover, like PC1, the average value of PC2 is strongly positive during all three major El Niños (2.51$\sigma$, 2.50$\sigma$, and 2.20$\sigma$), and it is therefore not a major contributor to the circulation differences among them.

That leaves PC3, which differs from the others in several important ways. First, whereas the first two PCs are primarily associated with tropical Pacific variability (Figs. 5d,e,g,h), PC3 projects most strongly in the Indian Ocean (Figs. 5f,i). Owing in part to the Madden–Julian oscillation, OLR anomalies in the Indian Ocean are not as strongly tied to SSTs as they are in the Pacific, which may contribute to the greater spread in PC3 among ensemble members. Second, while the first two PCs have about the same value during all three major El Niños, PC3 is much lower in 2015/16 than in 1982/83 or 1997/98, by about 2.5$\sigma$ on average ($-0.89\sigma \text{ vs } 1.56\sigma$ and 1.65$\sigma$). Third, the $Z_{200}$ pattern associated with PC3 variability (Fig. 5i) strongly resembles the pattern of differences in Figs. 4c,d. Finally, PC3 is strongly correlated with precipitation throughout California ($r = 0.44$ and 0.57 in the north and south, respectively; Table 1). These correlations are substantially larger than the correlation with PC1, implying that PC3 exerts an even stronger influence on California precipitation than canonical El Niño variability. Together, this body of evidence strongly indicates that SST-driven variability in PC3 is largely responsible for the ensemble-mean differences in both California precipitation and the large-scale atmospheric circulation between 2015/16 and the previous El Niños of 1982/83 and 1997/98.

If the SST pattern associated with PC3 (Fig. 5i) is responsible for the ensemble-mean differences in California rainfall between 2015/16 and previous strong El Niños, then eliminating differences in this SST pattern should cause the circulation differences to disappear. To test this hypothesis, we repeated the simulations of 1982/83, 1997/98, and 2015/16 but adjusted the SSTs in each case to compensate for the differences in PC3 among them (see appendix B). If this SST pattern is the primary cause of the ensemble-mean differences among the El Niños, then we should expect the perturbed-SST simulations of 1982/83 and 1997/98 to more closely resemble the observed-SST simulation of 2015/16, and we should expect the perturbed-SST simulation of 2015/16 to more closely resemble the observed-SST simulations of 1982/83 and 1997/98.

### Table 1. The Pearson correlation coefficient $r$ between the ensemble mean of each PC of tropical OLR (columns) and the ensemble-mean precipitation in Northern California (top row), Southern California (middle row), and the state as a whole (bottom row). The correlations are calculated over the entire 66-yr simulation period. Statistically significant correlations are in boldface.

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<th>PC1</th>
<th>PC2</th>
<th>PC3</th>
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<tr>
<td>Northern California</td>
<td>-0.05</td>
<td>0.36</td>
<td>0.44</td>
</tr>
<tr>
<td>Southern California</td>
<td>0.46</td>
<td>-0.08</td>
<td>0.57</td>
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<tr>
<td>All California</td>
<td>0.37</td>
<td>0.03</td>
<td>0.59</td>
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This hypothesis is confirmed in Figs. 6 and 7, which show the impact of the SST perturbations on California precipitation and $Z_{200}$, respectively. Focusing first on precipitation in the south (Fig. 6), we find that in 1982/83 and 1997/98, the SST perturbation causes significant drying relative to the unperturbed simulations (Figs. 6f,g vs Figs. 3d,e). In both cases, the ensemble-mean precipitation in the perturbed-SST simulations is close to average and statistically indistinguishable from the observed-SST simulations of 2015/16. Conversely, the opposite SST perturbation in 2015/16 causes a significant increase in Southern California precipitation equal to 33% of climatology, which is in statistical agreement with the observed-SST simulations of 1982/83 and 1997/98. In the north, similar changes in precipitation are observed in all perturbation experiments, but they are not statistically significant (Figs. 6a,b vs Figs. 3a,b).

Figure 7 tells a similar story in the context of the large-scale circulation. Its three panels show the change in ensemble-mean $Z_{200}$ in each of the perturbed-SST simulations relative to its unperturbed counterpart. In 1982/83 (Fig. 7a) and 1997/98 (Fig. 7b), the SST perturbation causes a significant increase in $Z_{200}$ across much of the Northern Hemisphere midlatitudes, while the opposite response is found in 2015/16 (Fig. 7c). As expected, the magnitude and spatial structure of these changes closely resemble the differences among the unperturbed simulations found in Figs. 4c,d. Together with the precipitation changes in Fig. 3b, these results provide strong support for our hypothesis that PC3 and its associated SST pattern significantly contributed to California’s dry winter in 2015/16 relative to previous strong El Niños, particularly in the southern part of the state.

Having established that the SST pattern in Fig. 5i likely contributed to the differences in California precipitation among the three El Niño events, it is natural to ask which components of this SST pattern may have played the greatest role. On one hand, it is clear that PC3 variability is likely driven in part by SST anomalies in the Indian and western Pacific Oceans, where the correlations with OLR and SST are strongest (Figs. 5f,i). However, nonzero correlations are also found in other basins, including the Atlantic and eastern Pacific, raising the possibility that SST differences in these regions may also have played a role.

To test the extent to which PC3 variability is driven by SST anomalies in the Indian Ocean/western Pacific (IWP), we repeated the perturbed-SST experiment from 2015/16, but this time using only the component of the SST perturbation within the IWP, which we define as the region enclosed by the green boundary in Fig. 5i. We also performed a complementary set of simulations, in which the 2015/16 SST perturbation was imposed

![Fig. 6](image-url)
everywhere in the tropics except the IWP. Figures 6i,j and 7d,e show the impact of these SST perturbations on Southern California precipitation and $Z_{200}$, respectively. In both fields, the response was only slightly weaker than when the global SST anomaly was imposed. For example, the increase in California precipitation was about 26% and 27% in the IWP and non-IWP simulations, compared with 33% for the full perturbation case. Similarly, the changes in $Z_{200}$ in the IWP and non-IWP simulations capture certain features of the full-perturbation response in Fig. 7c, but with lower magnitude and with some aspects of the spatial pattern absent. The results suggest that PC3 variability is not only influenced by SST anomalies in the IWP region but can also be driven by SST anomalies in the subtropical North Atlantic and eastern Pacific.

4. Possible cause of seasonal forecast errors

If the difference in California precipitation between 2015/16 and previous strong El Niño was driven in part by SST differences, why did seasonal forecast models predict similar precipitation anomalies for all three events (Fig. 2)? While the answer to this question is likely complex and model dependent, one likely contributing factor is evident in Fig. 8. Figure 8a shows the ensemble-mean bias in forecasts of wintertime tropical SSTs, while Figs. 8b–d show the time series generated by projecting SST anomalies from each winter onto the spatial patterns in Figs. 5g–i. We refer to these time series as PC1*–PC3* because they are analogous to the PCs in Figs. 5a–c but with the EOFs of OLR (Figs. 5d–f) replaced by the correlation maps between the original PCs and SST*, with SST* defined as the local SST departure from the tropical mean (30°S–30°N). Like the original PCs, PC1* and PC2* had similar values during all three major El Niños (green lines), while PC3* was about 3σ lower in 2015/16 than in 1982/83 and 1997/98.

To the right of each time series, we have plotted the full range of model forecasts for each PC* for the winter of 2015/16, which we calculated by projecting each SST forecast onto the correlation maps in Figs. 5g–i. The dashed blue lines to the right of the PC* time series represent the ensemble mean of each PC* forecast.

At first glance, the ensemble-mean SST bias pattern (Fig. 8a) does not strongly resemble any of the correlation patterns in Figs. 5g–i. As such, we would not necessarily expect systematic errors in forecasts of any of the PC*s. On closer inspection, however, we find that certain models do exhibit significant errors, particularly in their forecasts of PC3*. For example, of the six models considered in our analysis, only two models [COLA–Rosenstiel School of Marine and Atmospheric Science
RSMAS) CCSM4 and NASA GMAO model] give a range of PC3* forecasts that encompass the observed value, while the remaining forecasts were significantly too high. Across the full ensemble, the PC3* forecasts were off by an average of 1.65\(s\), which in light of Fig. 5o, could account for some of the forecast bias in California precipitation.

To further illustrate the impact of PC3* biases on California precipitation across the NMME, the lower panels of Fig. 8 show precipitation versus PC3* for each ensemble member in Northern (Fig. 8e) and Southern (Fig. 8f) California. Circles represent each of the 61 ensemble members, while diamonds represent the ensemble mean of each forecast model. Across the full ensemble, precipitation in Southern California (Fig. 8f) is significantly correlated with PC3* at \(r = 0.40\), with a regression slope of 0.19\% per standard deviation of PC3*. Given that observed SSTs showed a roughly 3\(\sigma\) difference in PC3* between 2015/16 and previous strong El Niños (Fig. 8d), this regression slope implies that 2015/16 should have been drier in Southern California by more than 50\% of climatology as a direct consequence of the observed difference in PC3*. This prediction is in good agreement with what we found in our prescribed-SST simulations (Fig. 3), suggesting that the relationship between PC3 and Southern California precipitation is likely robust and not just an unusual quirk of the GFDL AM2.1 model. Meanwhile, the relationship between PC3* and Northern California precipitation is quite weak across the NMME, which is also not surprising given the results of both the original and perturbed-SST simulations presented in Figs. 3 and 6. This evidence further supports the conclusion that, at least in Southern California, some of the NMME forecast bias in precipitation in 2015/16 was likely driven by SST biases related to PC3*.

5. Discussion

In this paper, we have analyzed an ensemble of prescribed-SST simulations to understand why the major El Niño of 2015/16 brought so much less rain to California than previous El Niños of comparable strength. Our results suggest that while internal atmospheric variability likely contributed to differences among the events, so too did SST differences outside of the canonical Niño-3.4 region. In the ensemble mean of the simulations, nearly all of the difference in wintertime California precipitation between 2015/16 and previous strong El Niños can be explained by the third principal component (PC3) of tropical convection. Variability in PC3 is most strongly associated with anomalous SSTs and convection in the Indian Ocean and western Pacific,
but our SST perturbation experiments suggest that other regions, such as the eastern equatorial Pacific and subtropical North Atlantic, likely also helped differentiate 2015/16 from previous strong El Niño. Given its high order and modest contribution to the total variance, PC3 seems unlikely to be a physical "mode" of the coupled climate system, in the sense that El Niño (i.e., PC1) arises from the coupled Bjerknes feedback. This might explain why NMME forecast models did a poor job of predicting the SST anomaly pattern associated with PC3 and California precipitation during the winter of 2015/16. Nevertheless, the statistical connection between PC3 and California precipitation is quite robust. Within the GFDL AM2.1 ensemble, for example, precipitation in both the north and the south correlates more strongly with PC3 than with the Niño-3.4 index (Table 1), challenging a common perception that El Niño is the dominant source of SST-driven variability in wintertime precipitation in California.

Since much of our analysis is based on simulations by a single model (GFDL AM2.1), it is possible that other models could point to different causes of California’s relative dryness in 2015/16. In the GFDL AM2.1 simulations, we have identified a circulation pattern common to the 2015/16 differences from both the 1982/83 and 1997/98 events (Figs. 4c and 4d, respectively). Like the observed differences (Figs. 4a,b), this circulation pattern has a large zonal-mean component in the midlatitudes, and our model experiments consistently relate it to the third PC of tropical OLR and its corresponding SST pattern. However, multimodel intercomparison is necessary to investigate the possible model dependency of this result.

Finally, the strong correlation between PC3 and SSTs in the Indian Ocean raises the possibility that recent warming trends may have contributed to the dry El Niño of 2015/16 in California. It is well known that the Indian Ocean has warmed at a faster rate than other basins in recent decades (e.g., Alory et al. 2007; Du and Xie 2008; Roxy et al. 2014). Indeed, in the eastern Indian Ocean, where the correlations with PC3 are strongest, SSTs set a new record for warmth in 2015/16, breaking the previous record set in 2002/03 by nearly 0.5°C (Fig. 9). Our analysis suggests that this warm anomaly likely contributed to the decrease in Southern California precipitation in 2015/16 relative to 1982/82 and 1997/98 (Fig. 6). Moreover, by altering the zonal-mean winds within the subtropical jet (Seager et al. 2003), secular warming in this region has been shown to produce zonally elongated ridges in the Northern Hemisphere midlatitudes (Hoerling and Kumar 2003; Lau et al. 2008), similar to the differences between 2015/16 and previous El Niños identified in this paper. Time will tell if the recent pattern of SST warming is a response to anthropogenic forcing or primarily the result of low-frequency natural variability (e.g., Tokinaga et al. 2012; Zhang and Karnauskas 2017). The answer could have important consequences for the future of California’s water resources.

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APPENDIX A

Estimating the SST Contribution to Observed Differences in Precipitation

If we assume that the GFDL AM2.1 ensemble accurately simulates both internal atmospheric variability and the atmospheric response to SST differences, then the ensemble-mean difference in precipitation between
two winters can be interpreted as the SST-driven contribution. Conversely, the contribution from internal variability is equal to the observed difference minus the SST-driven contribution. If we assume that the distributions of precipitation across the ensemble are roughly normal, then the range of uncertainty in the SST-driven contribution is given by

$$\Delta P_{\text{SST}} = \Delta P_{\text{ensemble}} \pm t \frac{s}{\sqrt{N-1}}, \quad (A1)$$

where $t$ is the $t$ statistic for a given confidence threshold (which we choose to be 90%), $N$ is the number of ensemble members (40), and $s$ is defined as

$$s = \sqrt{\sigma_{\text{Year1}}^2 + \sigma_{\text{Year2}}^2}, \quad (A2)$$

or the root-mean-square of the ensemble standard deviations for each of the two years being compared.

**APPENDIX B**

**Calculating the SST Perturbation Associated with Differences in PC3 among El Niño Events**

The SST perturbation experiments were designed to capture the differences in PC3 among the major El Niño winters. For the 1982/83 and 1997/98 experiments, the SST perturbation was equal to the regression slope of SST* onto PC3, times the difference in PC3 relative to 2015/16 (about $-2.5\sigma$ in each case). For the 2015/16 experiment, the SST perturbation was identical to that of 1997/98, but with the opposite sign. These SST perturbations are closely related to the correlation pattern in Fig. 5i, since the regression slope is equivalent to the correlation scaled by the standard deviation of SST* at each grid point.

**REFERENCES**


