Contrastive Influence of ENSO and PNA on Variability and Predictability of North American Winter Precipitation

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ABSTRACT

In this work, the roles of El Niño–Southern Oscillation (ENSO) in the variability and predictability of the Pacific–North American (PNA) pattern and precipitation in North America in winter are examined. It is noted that statistically about 29% of the variance of PNA is linearly linked to ENSO, while the remaining 71% of the variance of PNA might be explained by other processes, including atmospheric internal dynamics and sea surface temperature variations in the North Pacific. The ENSO impact is mainly meridional from the tropics to the mid–high latitudes, while a major fraction of the non-ENSO variability associated with PNA is confined in the zonal direction from the North Pacific to the North American continent. Such interferential connection on PNA as well as on North American climate variability may reflect a competition between local internal dynamical processes (unpredictable fraction) and remote forcing (predictable fraction). Model responses to observed sea surface temperature and model forecasts confirm that the remote forcing is mainly associated with ENSO and it is the major source of predictability of PNA and winter precipitation in North America.

1. Introduction

It has been well documented that El Niño–Southern Oscillation (ENSO) is important in global short-term climate variability and predictability (National Research Council 2010), for example, for surface air temperature and precipitation variability in North America (Ropelewski and Halpert 1987; Hu and Feng 2001, 2012; Mo 2010; Deser et al. 2018; Peng et al. 2018, 2019). For the seasonal climate variations in North America, the impact of ENSO is mainly through an atmospheric

teleconnection, which is similar to the Pacific–North American (PNA) pattern (Wallace and Gutzler 1981; Barnston and Livezey 1987; Ning and Bradley 2014, 2015; Coleman and Rogers 2003; Dominguez and Kumar 2005). The coherent variation of the PNA- and the ENSO-driven atmospheric circulation anomaly is evident for the similarity of the simultaneous correlation patterns of December–February (DJF) precipitation in North America with the PNA and Niño-3.4 indices, respectively (Figs. 1a,b).

Nevertheless, there are distinct differences between PNA- and ENSO-driven atmospheric responses, which have been argued by Straus and Shukla (2000, 2002). They noted that compared to non-ENSO winters, there is a shift in the probability of occurrence of a PNA-like pattern in El Niño and La Niña winters. Meanwhile, the

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FIG. 1. Simultaneous correlations of DJF precipitation anomalies with the (a) PNA, (b) Niño-3.4, and (c) ENSO-unrelated PNA indices. Hatching represents significant correlations at the significance level of 95% using the t test.

PNA spatial pattern is modified by tropical forcings, such as ENSO. Thus, for the PNA-associated variability, there are two components: one is driven by the tropical heating, and the other is produced by the atmospheric internal dynamic processes. It is necessary to distinguish the two components and further identify the contrastive impacts of ENSO and PNA (in particular, the component generated by the atmospheric internal dynamic processes) on the winter precipitation variability in North America through examining the similarities and differences of ENSO- and PNA-associated atmospheric

circulation. Also, it is necessary to further clarify the contributions of ENSO and PNA to the winter precipitation predictability in North America through assessing climate model simulations and forecasts.

In this work, we further examine the statistical contribution of ENSO to the PNA and the associated atmospheric circulation, with a focus on the contrastive impact of ENSO and PNA on variability and predictability of winter precipitation in North America by using analysis/reanalysis data and climate model simulations and forecasts. As in [Hu et al. \(2005\)](#), the PNA

index is first separated into two parts through linear regression: ENSO-related and ENSO-unrelated components. Then the contrastive connections of the two parts of the PNA with the atmospheric circulation as well as sea surface temperature (SST) anomalies are examined. Furthermore, through examining the response of North American winter precipitation to observed global SST in a global climate model as well as in hindcasts and forecasts from a coupled climate model, the connection of predictability of the precipitation with SST forcing is further examined and the source of the predictability is attributed. The rest of the paper is organized as follows: The data used in this work are introduced in [section 2](#); the contrastive influences of ENSO and PNA on the variability and predictability of PNA and North American winter precipitation are shown in [sections 3](#) and [4](#), respectively. A summary and discussion are given in [section 5](#).

2. Data

Monthly mean atmospheric data are derived from the reanalysis of the National Centers for Environmental Prediction (NCEP)–National Center for Atmospheric Research (NCAR; [Kalnay et al. 1996](#)). The monthly mean geopotential heights at 500 hPa (H500) and at 200 hPa (H200) for the period January 1950 to February 2018 at $2.5^\circ \times 2.5^\circ$ resolution are used in this study. (Monthly mean PNA index time series are downloaded from <http://www.cpc.ncep.noaa.gov/products/precip/CWlink/pna/norm.pna.monthly.b5001.current.ascii.table>.) The monthly mean PNA index was constructed by following the modified pointwise method ([Wallace and Gutzler 1981](#)):

$$\begin{aligned} \text{PNA} = & [\text{H500}*(15^\circ-25^\circ\text{N}, 180^\circ-140^\circ\text{W}) \\ & - \text{H500}*(40^\circ-50^\circ\text{N}, 180^\circ-140^\circ\text{W}) \\ & + \text{H500}*(45^\circ-60^\circ\text{N}, 125^\circ-105^\circ\text{W}) \\ & - \text{H500}*(25^\circ-35^\circ\text{N}, 90^\circ-70^\circ\text{W})]/4, \end{aligned}$$

where H500* denotes normalized monthly mean H500 anomaly from the NCEP–NCAR reanalysis.

Monthly mean SST on a $2^\circ \times 2^\circ$ grid is from ERSST version 5 (ERSSTv5; [Huang et al. 2017](#)). The Niño-3.4 index is defined as the averaged ERSSTv5 SST anomalies in the region (5°S – 5°N , 170° – 120°W) to represent ENSO (downloaded from <http://www.cpc.ncep.noaa.gov/data/indices/ersst5.nino.mth.81-10.ascii>). Monthly mean precipitations of [Chen et al. \(2002\)](#) are analyzed; these cover the period from January 1950 to February 2018 and have a $1^\circ \times 1^\circ$ spatial resolution.

To examine the impact of global SST on the predictability and variability of North American winter precipitation, Atmospheric Model Intercomparison Project (AMIP)-like experiments are analyzed. The atmospheric general circulation model is the atmospheric component [Global Forecast System (GFS)] of the Climate Forecast System, version 2 (CFSv2), from NCEP ([Saha et al. 2014](#)). Forced by observed global SST, the model is integrated from January 1957 to February 2018 with 18 ensemble members by slightly different atmospheric initial conditions ([Hu et al. 2017a](#); [Liang et al. 2019](#)).

The prediction skills of winter precipitation in North America are examined with retrospective predictions (or hindcasts) for January 1982–February 2011 and real-time predictions (or forecasts) for March 2011–December 2017 from CFSv2 ([Saha et al. 2014](#)). The ensemble mean analyzed here is the average of 20 ensemble members, which were made every 5 days with ocean and atmospheric initial conditions (ICs) from the NCEP Climate Forecast System Reanalysis (CFSR; [Saha et al. 2010](#)).

3. Constructive influence of ENSO and PNA on the variability

a. Connection of winter precipitation in North America with PNA and ENSO

Based on linear regressions, the winter (DJF) PNA index during 1950/51–2017/18 is first separated into the ENSO-related part and the ENSO-unrelated part ([Fig. 2](#)). The ENSO-related part is computed by a simultaneous linear regression of the total PNA index with respect to the Niño-3.4 index ([Peng et al. 2014](#)). The ENSO-unrelated part ([Fig. 2c](#)) is derived as the difference between the total PNA index ([Fig. 2a](#)) and the ENSO-related part ([Fig. 2b](#)). The assumption of the method separating the ENSO-related and ENSO-unrelated parts here is that the relationship between PNA and ENSO is linear. The scatterplot suggests that the linear assumption is reasonable with the linear correlation of 0.53 between the Niño-3.4 and PNA indices during DJF 1950/51–DJF 2017/18 ([Fig. 3](#)). [Zhang et al. \(1996\)](#) noted that temporal variation of the dominant mode of SST anomalies over the North Pacific is almost linearly independent on ENSO and it is mainly coupled with local atmosphere. [Schneider et al. \(2003\)](#) also argued that atmospheric responses in the extratropics to the tropical SST forcing are nearly linear. From the linear separation, on average, about 29% of PNA variance is linearly associated with ENSO, and 71% cannot be explained by the linear relation with ENSO, which is generally consistent with [Zhang et al. \(1996\)](#).

FIG. 2. (a) Total, (b) ENSO-related part, and (c) ENSO-unrelated part of DJF PNA index during 1950/51–2017/18.

Nevertheless, the fraction of the variance of PNA explained by ENSO should vary with ENSO event, which deserves further investigation. Thus, although the ENSO and PNA are physically connected (Straus and Shukla 2000, 2002; Yu and Zwiers 2007), most of the variability of the PNA seems not to be forced by ENSO. That is also evident in the correlation pattern as shown in Fig. 1. It is noted that all the correlation patterns feature a typical north–south contrast, but the correlation pattern with the PNA index (Fig. 1a) is more similar to that with the ENSO-unrelated PNA index (Fig. 1c) than that with the Niño-3.4 index (Fig. 1b), particularly

in the southwestern United States and northeastern part of North America.

By checking the lead–lag correlation between monthly mean Niño-3.4 and PNA indices, it is seen that the maximum correlation is slightly smaller than 0.3 and it occurs when the PNA index lags the Niño-3.4 index by 1–2 months (Fig. 4a). This time lag may suggest that partial variability of PNA pattern is forced by ENSO. Furthermore, the persistence of the two indices is profoundly different (Fig. 4b). The Niño-3.4 index has a much longer persistence than the PNA index. The positive lagged autocorrelation extends to 10 months for the

FIG. 3. Scatterplots of the PNA and Niño-3.4 indices during DJF 1950/51–DJF 2017/18. The linear correlation is 0.53.

Niño-3.4 index (bars in Fig. 4b), while it is only 3 months for the PNA index (curve in Fig. 4b). Such short persistence for the PNA index is somewhat similar to the variability of the high-frequency portion of the Pacific decadal oscillation (PDO; Davis 1976; Kumar et al. 2013). Kumar et al. (2013, see their Fig. 3a) noted that the lagged autocorrelation for monthly variability of PDO index defined based on empirical orthogonal function (EOF) analysis of H200 anomalies is significant only for first 3 months. Nevertheless, the lagged autocorrelation results of Kumar et al. (2013) might rely on the choice of PDO index to some extent. They noted that the SST-based PDO index has longer persistence than the index based on atmospheric fields. These results are an indication of the feature that the extratropical climate variability at seasonal–interannual time scales (such as PNA) may be partially driven by tropical forcing (such as ENSO) and local air–sea interaction (Lau and Nath 1996; Hu et al. 2011; Peng et al. 2014, 2018, 2019), although it may be mainly driven by internal dynamical processes.

To examine the connection of the ENSO-related and unrelated parts of the PNA with the atmospheric circulation, Fig. 5 (shading) shows the linear correlation between H200 and the PNA index. A forced wave pattern, similar to the PNA pattern but with a tropical origin, is seen in Figs. 5a and 5b with large positive correlations in the tropics. The H200 anomalies associated with the ENSO-unrelated part of PNA index are mainly confined in the extratropics (Fig. 5c), and there are no significant correlations in the tropics, implying that the ENSO-unrelated PNA variability may not be

mainly driven by the tropical forcing. The results are similar if H500 instead of H200 is used (not shown).

b. Role of remote forcing

To explain the midlatitude response to tropical heating, Rossby wave propagation forced by convective heating anomalies is a straightforward mechanism to be used (e.g., Hoskins and Karoly 1981; Jin and Hoskins 1995; Peng et al. 2014). ENSO-associated tropical convection variability is a major source of such heating anomalies. Propagation of the forced stationary wave can be diagnosed by wave activity flux that is derived for linear, quasigeostrophic disturbances on a zonal flow. Here, following Wu et al. (2003), the wave activity flux from H200 anomaly is computed:

$$\begin{aligned}
 F_s &= (F_\lambda, F_\varphi) \\
 &= \sigma \cos \varphi \left[\bar{v}^* 2 - \frac{1}{2 \Omega a \sin 2 \varphi} \frac{\partial}{\partial \lambda} (\bar{u}^* \bar{\Phi}^*), -\bar{u}^* \bar{v}^* \right. \\
 &\quad \left. + \frac{1}{2 \Omega a \sin 2 \varphi} \frac{\partial}{\partial \lambda} (\bar{u}^* \bar{\Phi}^*) \right], \quad (1)
 \end{aligned}$$

where σ = pressure/1000 hPa, (λ, φ) are longitude and latitude, (u, v) are the horizontal geostrophic velocities from the geopotential height Φ , and Ω and a are Earth's rotation rate and radius, respectively. The overbar (asterisk) indicates the time mean (the departure from the zonal mean). Divergence (convergence) of the wave activity fluxes links to a source (sink) of stationary wave activity (Karoly et al. 1989; Wu et al. 2003; Hu et al. 2005).

From Fig. 5b (arrows), we note a meridional propagation with a divergence of wave activity flux in the western and central tropical Pacific and a convergence in the North American continent, consistent with the influence of ENSO on North American winter climate demonstrated in previous works (e.g., Ropelewski and Halpert 1987; Peng et al. 2018, 2019). On the other hand, for the wave activity flux associated with the ENSO-unrelated part of PNA (arrows in Fig. 5c), it mainly features a zonal propagation pattern with the divergence of wave activity flux in the mid–high latitudes of the North Pacific and convergence in the North American continent. The overall intensities of the divergence and convergence are stronger for that associated with the ENSO-unrelated part than that associated with the ENSO-related part of PNA (arrows in Fig. 5).

As expected and consistent with the wave activity flux (Fig. 5b), the ENSO-related part of PNA variation is significantly correlated with SST anomalies in the Pacific

FIG. 4. (a) Lead-lag correlation between monthly mean Niño-3.4 and PNA indices and (b) lagged autocorrelation of monthly mean Niño-3.4 (bar) and PNA (curve) indices in January 1950–December 2017. The horizontal line represents the t test at 95% level with independent sample sizes following Bretherton et al. (1999). The red (black) horizontal line in (b) is the test for the Niño-3.4 (PNA) index.

Ocean, as well as in the Indian Ocean and the tropical North Atlantic Ocean (shading in Fig. 6b), a conventional SST distribution associated with El Niño (Klein et al. 1999). Corresponding to the profound SST anomalies in the tropical Pacific Ocean, atmospheric circulation (H200) anomalies are the ENSO-forced PNA-like teleconnection pattern (contour in Fig. 6b; Straus and Shukla 2000, 2002). The maximum correlations (larger than 0.8) exist in the eastern

tropical Pacific, implying a tropical origin and an association with ENSO. Previous works have well demonstrated the influence of the tropical Pacific (such as ENSO) on the extratropical Northern Hemisphere mainly through the Rossby wave train forced by tropical diabatic heat anomalies (e.g., Hoskins and Karoly 1981; Ting and Sardeshmukh 1993; Deser and Blackmon 1995; Jin and Hoskins 1995; Lau and Nath 1996).

FIG. 5. Simultaneous correlations between H200 anomalies and DJF PNA index (shading) and simultaneous regression of the wave activity fluxes of H200 anomalies (arrows) with respect to normalized DJF PNA index for (a) total, (b) ENSO-related part, and (c) ENSO-unrelated part of DJF PNA index in 1950/51–2017/18.

For the ENSO-unrelated part of the PNA, it is mainly associated with SST anomalies in the North Pacific that partially may be linked to the PDO (Fig. 6c). It is known that in addition to the interdecadal-time-scale variation, the PDO actually fluctuates on shorter time scales as well, such as interseasonal–interannual time scales (Hu and Huang 2009). For the corresponding correlations with H500 anomalies (contour in Fig. 6c), the maximum positive and negative correlations present over the

North American continent and the North Pacific have an amplitude larger than 0.6, while along the equatorial Pacific, the correlations are minimum with an amplitude smaller than 0.2. That is consistent with wave activity flux (Fig. 5c) and implies a disconnection with the tropical forcing (ENSO) to some extent. Thus, the variability of the PNA pattern may have two distinct components. About 30% of the variance is forced by ENSO, which may be predictable because of the high predictive

FIG. 6. Simultaneous correlations of SST (shading) and H500 (contour) anomalies with (a) total, (b) ENSO-related part, and (c) ENSO-unrelated part of PNA index in DJF. Hatching represents significant correlations at the significance level of 95% using the t test for the correlations of SST anomalies with the PNA index. Contour interval is 0.2.

skill of ENSO. For the ENSO-unrelated part of the PNA variability (about 70% of the variance), it is partially associated with an SST anomaly in the North Pacific that has lower predictability than ENSO (Kumar et al. 2013; Hu et al. 2014), and it largely reflects internal variability. The low predictability is due to the fact that the PDO-like SST anomaly pattern mainly reflects an oceanic response to the atmospheric cyclonic circulation in the eastern North Pacific, with the alongshore wind promoting an oceanic downwelling and the surface cooling roughly collocating with the cyclonic center. The process is consistent with

Kumar et al. (2013, their Fig. 3b) who indicated that the atmospheric circulation anomaly in the North Pacific leads the PDO-like SST anomaly pattern by a few months.

4. Contrastive influence of ENSO and PNA on the predictability

a. Predictability

Here, to estimate the impact of SST on climate variability and predictability (Peng et al. 2000; National Research Council 2010), AMIP-like model experiments

FIG. 7. DJF precipitation in the AMIP runs in 1957/58–2017/18: (a) anomalous correlations between observations and the ensemble mean of the AMIP runs with 18 ensemble members; (b) perfect model score, which is referred to as averaged correlation of each individual member with the ensemble mean of the other 17 members in the AMIP runs; and (c) signal-to-noise ratio (SNR) of the AMIP runs with 18 ensemble members. The hatched regions in (a),(b) represent the correlations significant at 95% or higher confidence level using the t test, and in (c) is for values larger than or equal to 0.5.

are analyzed to further validate the predictability of North American winter precipitation as well as the roles of ENSO and PNA. Figure 7a shows the precipitation anomaly correlations between the observations and model simulations of 18-member ensemble means in DJF. Significant positive correlations are present in southwestern, southeastern, northwestern, and northeastern North America. Some significantly negative correlations

are seen west of Lake Superior. The correlations are relatively small and not significant in the middle of the United States along 40°N. These results confirm that the impact of SST (ENSO) on North American winter precipitation is largely regionally dependent (Ropelewski and Halpert 1987; Peng et al. 2018, 2019).

With the perfect model assumption, we use the perfect model score (PMS) to approximate the predictability.

The PMS is referred to as the mean of the correlations of each individual member with the mean of the remaining 17 ensemble members (Liang et al. 2019). All PMSs are positive but mostly smaller than 0.5 (Fig. 7b). The spatial pattern of PMSs (Fig. 7b) is somewhat similar to the correlation shown in Fig. 7a, with significant positive values in the southwestern, southeastern, northwestern, and northeastern North America. These regions correspond well to the regions with large values of variance explained by the PNA index and/or the Niño-3.4 index [Fig. 8, also see Fig. 3 of Leathers et al. (1991); Fig. 8 of L'Heureux et al. (2015); Fig. 1 of Wise et al. (2015)]. Such spatial coherence further suggests that most of the predictability and prediction skill (Figs. 7a,b) come from PNA, particularly the component associated with ENSO.

Nevertheless, in addition to the regional dependence of the significance, overall the correlations and PMSs are small, implying the importance of other processes, such as internal dynamical processes, stratosphere, and land–atmosphere interaction (National Research Council 2010; Deser et al. 2018). Figure 7c shows the signal-to-noise ratio (SNR) of the AMIP runs. Here, the signal is defined as the standard deviation of the ensemble mean of all 18 members, and the noise is defined as the standard deviation of the spread of the individual members from the ensemble mean. Large (small) SNR is linked to the expected high (low) skill of the forecast or high (low) predictability [see Fig. 2 of Kumar and Hoerling (2000); Fig. 9 of Kumar et al. (2017)]. The similarities of spatial distribution in Figs. 7a–c suggest that SST anomalies associated with ENSO are likely the major forcing associated with predictability. Nevertheless, since the AMIP runs include all other aspects of SST variability in the global oceans, SST anomalies in the other ocean basins may play a role as well.

On the other hand, small SNR (mostly smaller than 0.4; Fig. 7c) indicates that the local atmospheric internal dynamics is more important than the remote/boundary forcing (SST) in generating precipitation in North American winter, indicating its low predictability in nature. That is consistent with, for example, Kumar and Chen (2017) regarding the predictability of California winter precipitation and Liang et al. (2019) regarding the predictability of summer rainfall in eastern China. In fact, this is a common and basic feature of climate variability over the mid–high-latitude lands or oceans (Davis 1976; Hu et al. 2011, 2017a; Liang et al. 2019), where the variations are dominated by local atmospheric internal variability and, to a minor extent, constrained by remote forcings, such as ENSO and SST in the tropics (Deser et al. 2018).

FIG. 8. Percentage of the variance of observed DJF precipitation anomalies in 1950/51–2017/18 explained by the total (a) PNA and (b) Niño-3.4 indices. The hatched regions represent the explained variance fractions larger than or equal to 15%.

b. Prediction skill

To further verify the contrastive influences of the ENSO and PNA on the predictability of winter precipitation variations in North America, using forecasts from CFSv2 as an example, its forecast skill (measured by linear correlation coefficient) of winter (DJF) precipitation anomaly is shown in Fig. 9. It is seen that positive correlations are dominant, although some negative correlations are present in some regions. The correlation pattern in North America is similar for different lead-time forecasts, and overall forecast skill decreases when lead time increases. Such a pattern is similar to the results of multimodels (see Fig. 5 of Becker et al. 2014).

Taking a one-month lead forecast as an example (Fig. 9a), the high skill is in the southwestern and southeastern portions of North America, and some moderate skill exists in the northeastern region of North America and the Great Lakes. Negative correlations are

FIG. 9. Correlations between observed and CFSv2 predicted winter (DJF) mean precipitation anomalies in North America with ICs in January 1982–December 2017 in (a) 1, (b) 3, (c) 5, and (d) 7 month leads. Shading intervals are 0.2.

also visible, mainly in the central part of North America. This spatial distribution pattern has high similarities with that of the AMIP run results as well as that of the percentage of variance of winter precipitation explained by the Niño-3.4 index in the observations (Figs. 7, 8b). The similarity further confirms that the predictability and prediction skill of winter precipitation in North America are dominated by the influence of ENSO. It is noted that the Ohio Valley region has relatively high correlations with both the PNA and Niño-3.4 indices (Fig. 8), but CFSv2 prediction skill is relatively low (Fig. 9), which may be due to model biases. As shown in Fig. 10, for example, the loading of H500 EOF2 in the Ohio Valley region is smaller in CFSv2 (Fig. 10h) than in the observations (Fig. 10f).

5. Summary and discussion

In this work, we examine the role of ENSO in the variability and predictability of the PNA and precipitation anomalies in North America in winter. It is

noted that 29% of the variance of PNA is linked to ENSO during winter 1950/51–2017/18 and thus may be largely predictable. The remaining 71% of the variance of PNA is associated with atmospheric internal variability and SST anomalies in the North Pacific, which may be largely unpredictable. That is consistent with the low predictive skill of U.S. rainfall in a climate forecast system (Zhu et al. 2013) and low predictability of winter precipitation in North America suggested by AMIP-like simulations. That is a common and basic feature of climate variability over the mid–high latitudes, where the variations are dominated by local atmospheric internal variability and, to a minor extent, constrained by remote forcings, such as SST in the tropics associated with ENSO.

Specifically, the ENSO impact is mainly meridional from the tropics to the mid–high latitudes, while the connection between the North Pacific and the North American continent is mainly confined in the zonal direction, resembling a PDO pattern. Interferential connection of ENSO and PDO on PNA as well as North

FIG. 10. (a) PC1, (b)–(d) EOF1, (e) PC2, and (f)–(h) EOF2 of H500 anomalies in (0° – 80° N, 120° – 360° E) during DJF 1982/83–DJF 2016/17. In (a), (e), shading, bar, and line represent the results of NCEP–NCAR, AMIP, and CFSv2, respectively. (b), (f); (c), (g); and (d), (h) are EOF1/EOF2 of NCEP–NCAR, AMIP, and CFSv2, respectively. Shading intervals are 0.2.

American climate variability and predictability may reflect a competition of local internal dynamical processes (unpredictable part) and remote forcing (predictable part) (Kumar et al. 2013; Kumar and Chen 2017; Deser et al. 2018).

The SNR of winter precipitation in North America is mostly smaller than 0.4, indicating that the local atmospheric internal dynamics is more important than remote/boundary forcing (SST) in generating the precipitation in North American winter and implying that its predictability is low in nature. The model responses to observed SST and model forecasts confirm that the predictability and prediction skill of winter precipitation in North America are dominated by the influence of ENSO, and the skill is low and largely regionally dependent.

It is obvious that biases in the AMIP simulations, CFSv2 forecasts, and even in the reanalysis data (Kumar and Hu 2012; Liang et al. 2019) may affect the results to some extent. Figure 10 is an example that shows the EOF analysis of H500 anomalies in the reanalysis, AMIP simulation, and CFSv2 forecasts. It is seen that although spatial patterns of EOF1 of the NCEP–NCAR reanalysis, AMIP simulations, and CFSv2 forecasts are similar, they are not identical. Compared with EOF1, the differences of EOF2, the corresponding principal components (PC1 and PC2), and the fractions of variances explained by each mode are more visible among the reanalysis, AMIP simulations, and CFSv2 forecasts. It is obvious that such differences may quantitatively affect the assessment of prediction skill and predictability to some extent.

It should also be indicated that the linear regressions or correlations of PNA with respect to the Niño-3.4 index as well as atmospheric circulation and SST anomalies may not necessarily capture the complicated and comprehensive influence of ENSO on PNA for two reasons. First, the influence of ENSO on the extratropics may be partially nonlinear, and the impact on the cold and warm events of ENSO may not be symmetric because both the amplitude and duration of ENSO are asymmetric between the cold and warm phases of ENSO (Hoerling et al. 1997; An and Jin 2004; Hu et al. 2017b). Second, the spatial and subseasonal variations of the PNA pattern may not be precisely reflected in the monthly mean PNA index used in this work. Last, here we focus on the winter climate variability and predictability; the seasonal dependence is another interesting topic for future study.

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