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Bulk Connectivity of Global SST and Land Precipitation Variations

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Abstract

The land climate predictability at seasonal and interannual time scales is largely due to the influence of the ocean. The connections between global sea surface temperature anomaly (SSTA) and precipitation anomaly over land as a whole are assessed using observations and Atmospheric Model Intercomparison Project (AMIP) simulations for 1957-2018 in this work. With a novel bulk connectivity matrix, the regions of SSTA having the most significant connections with global land precipitation anomaly are identified and the seasonal evolution is evaluated. The similarities and differences between the observations and AMIP simulations are examined.

In both observations and AMIP simulations, SSTA in the tropical central and eastern Pacific connects strongly with the global land precipitation anomaly. Compared with that in the tropical Pacific, the connections with SSTA along the equatorial Indian and Atlantic Oceans are weaker. However, the seasonal evolution of the connection shows distinguished patterns between the observations and the AMIP simulations with the strongest (weakest) connections in October (June) in the observations, in March and October (June) in a single-member of the AMIP simulation, and in February (June) in the 17-member ensemble mean of the AMIP simulations. The ensemble averaging enhances the strength of the connectivity and improves its seasonality. The results of the bulk connectivity matrix in this work can serve as a benchmark to evaluate the connection of SSTA with global land precipitation variation in climate models.

I. Introduction

Climate anomaly, such as severe drought and flood, may cause casualty of people's life and loss of property. Thus, it is of vital importance both for the economy and the society to successfully predict the climate anomaly. It has been well documented that for seasonal and interannual climate variability, boundary forcing, particularly sea surface temperature (SST), is one of the key drivers and the major source of predictability (National Research Council 2010; Hu et al. 2020b). The oceans, particularly the tropical Pacific Ocean associated with different flavors of El Niño-Southern Oscillation (ENSO; Sarachik and Cane 2010; Ashok et al. 2007; Kao and Yu: 2009; Kug et al. 2009; Hu et al. 2012, 2019a; 2020a), affect global climate through various teleconnections (Bjerknes 1969; Wallace and Gutzler 1981; Yulaeva and Wallace 1994; Alexander, et al. 2009; Anderson et al. 2015; Stan et al. 2017; Yeh et al. 2018; Agarwal et al. 2019; Boers et al. 2019; Ekhtiari et al. 2019). For example, ENSO affects temperature and precipitation anomalies in North America by altering the meridional location of the mid-latitude jet stream (Yang et al. 2002; Leathers et al. 2018; Li et al. 2019). Through the ENSO-induced atmospheric circulation anomalies which have a spatial structure similar to the Pacific-North American (PNA) pattern, the jet stream in the eastern North Pacific and North America is shifted southward (northward) in the warm (cold) phase of ENSO (e.g., Wallace and Gutzler 1981; Leathers et al. 1991, 2018; Yang et al. 2002; Li et al. 20019). In East Asia, the impact of ENSO manifests in multiple ways. The summer climate in East Asia can be affected by ENSO through the modulation of the subtropical high in the western North Pacific as the Rossby-wave response to the diabatic heating associated with ENSO (e.g., Wang et al. 2000; Wu et al. 2003), the Pacific-Japan (PJ) pattern forced by the convective activities in the western tropical Pacific (e.g., Nitta 1987; Nitta and Hu 1996), or the Indo-Western Pacific Ocean capacitor effect (Xie et al. 2016). In southern Africa, ENSO influences the climate variability by modulating the tropical convection over the

subcontinent (e.g., Mason 2001). The anomalous precipitation in northeastern Brazil can partly be a response to warming in the northern tropical Atlantic a few months after the El Niño peak, as well as a shift of the Walker circulation (e.g., Kayano et al. 1988). Similarly, the ENSO influence on the Indian summer monsoon is mainly mediated through a longitudinal displacement and strength variation of the Walker circulation (e.g., Ju and Slingo 1995).

These impacts of SST anomaly (SSTA) on climate variability largely lay down the foundation for skillful prediction of seasonal-interannual climate anomalies (National Research Council 2010). SSTAs in the tropical Pacific associated with ENSO are the largest contributor to skillful climate prediction in many regions (Quan et al. 2006; O’Lenic et al. 2008; Peng et al. 2012; 2013; He et al. 2016; Liang et al. 2019; Huang et al. 2019). Goddard and Dilley (2005) noted that on average, the seasonal climate forecasts are more accurate during ENSO years than during ENSO-neutral years. Nevertheless, for monthly mean climate (temperature and precipitation) variability over the extratropical land, the influence of boundary forcing (such as SST in the tropical eastern and central Pacific, which is largely predictable) is small, it is mainly driven by the atmospheric internal dynamics at the seasonal-interannual time scales (e.g., Deser et al. 2018). The large internal variability leads to low prediction skill and predictability (e.g., Quan et al. 2006; Peng et al. 2012, 2013; Kosaka et al. 2012; He et al. 2016; Liang et al. 2019; Hu et al. 2020b; Liu et al. 2021). Thus, it is a challenge for climate models in capturing the effects of SSTs over land precipitation (e.g., Dittus et al. 2018). Given the facts that monthly mean precipitation is one of the most important climate variables of societal relevance and that its predictability at seasonal-interannual time scales is mainly controlled by the SST variability, it is necessary to examine the connection between monthly mean precipitation and SST anomalies at seasonal-interannual time

scales. That is beneficial to improve the precipitation forecast and to identify the flaw in climate models in capturing the connection between the SST and precipitation variations.

Recently, Hu et al. (2020b) examined the role of SSTA in determining the monthly mean precipitation variability over land. They proposed a new matrix to measure the bulk connectivity (BC) between global SST and global land precipitation anomalies and examined the spatial distribution of BC in all months of observations. In this work, to complement and expand the analysis of Hu et al. (2020b), with the BC matrix, we further assess the monthly evolution of the impact of SSTA on the variability and predictability of land precipitation at seasonal-interannual time scales. Specifically, with observational data and the Atmospheric Model Intercomparison Project (AMIP) simulations, we focus on the following questions: (a) In which regions of SSTAs have the most significant connection with global land precipitation anomaly as a whole? (b) What is the seasonal evolution of the connection? In other words, is the connection the strongest (weakest) in boreal winter (spring) as expected from the ENSO seasonality? (c) What is the predictability of the global land precipitation anomaly as a whole and what is its seasonal variation from the AMIP perspective? Moreover, such an assessment can set up a benchmark for climate model verification in capturing the bulk connection between global SSTA and land precipitation variation and then identifying models' fidelity and biases. The rest of the paper is organized as follows: The data and methods used in this work are introduced in section 2; the results of the observations and AMIP simulations are shown in sections 3 and 4, respectively. Summary and discussion are given in section 5.

2. Data and Methods

The observation-based data sets used in this work include the monthly mean SST fields from the UK Met Office Hadley Centre's sea ice and SST version 2 (HadISSTv2) on a $1^\circ \times 1^\circ$ grid during January 1870–December 2018 (Rayner et al. 2006). HadISSTv2 analysis includes in situ sea-surface observations and satellite-derived estimates at the sea surface with bias correlations of the bucket observations from 1870 through 1941. The monthly mean precipitation over land is from the Climatic Research Unit (CRU) on a $2^\circ \times 2^\circ$ grid during January 1901–December 2018. The precipitation data is derived from the interpolation of monthly climate anomalies from extensive networks of weather station observations (Harris et al. 2020).

As a robustness check, the Extended Reconstructed SST Version 5 from January 1854 to December 2018 on a $2^\circ \times 2^\circ$ grid (ERSSTv5; Huang et al. 2017) and the monthly mean reconstructed precipitation analysis from January 1948 to December 2018 on a $1^\circ \times 1^\circ$ spatial resolution (PRECP; Chen et al. 2002) are also examined. ERSSTv5 was derived from the International Comprehensive Ocean–Atmosphere Dataset (ICOADS), Argo floats above 5 meters, and HadISSTv2 ice concentration through the reconstruction of Empirical Orthogonal Teleconnections (EOTs). PRECP was developed by the optimal interpolation of gauge observations over the land only.

The AMIP simulations forced by observed SST can provide a benchmark for estimating the impact of SST on the atmosphere (such as precipitation). The AMIP simulations analyzed in this work include 17 ensemble members with slightly different atmospheric initial conditions and cover the period from January 1957 to December 2018 (Hu et al. 2020b). The atmospheric model used in the AMIP simulations is the Global Forecast System (GFS), which is the atmospheric component of version 2 of the Climate Forecast System (CFSv2; Saha et al. 2014). GFS has a horizontal resolution of T126 (~ 105 km) and 64 vertical levels. The model is forced by the

observed time-varying global monthly mean SSTs and sea ice from HadISST datasets for 1957-2008 (Rayner et al. 2006) and the Optimum Interpolation SST version 2 (OISSTv2) afterward (Reynolds et al. 2002).

In the following analyses, the common period (January 1957-December 2018) of the observation-based data and AMIP simulations is analyzed. The anomalies are calculated with respect to the climatology of January 1981-December 2010. For comparison, all data used in this work are interpolated into a $2^\circ \times 2^\circ$ grid before the calculations. To focus on interannual variation, a 10-year high pass filter and de-trending are applied to the data prior to the following calculations to suppress the influence of decadal and longer-time variations, as well as the long-term trend.

Following Hu et al. (2020b, see their Fig. 5), we define BC as a quantitative measure of the integrated connection of SSTA (variable-A) at an oceanic grid point (O_i, O_j) with precipitation (variable-B) at a global land grid point (L_m, L_n):

$$BC_{(O_i, O_j)} = \frac{100}{N \times M} \sum_{L_m=1}^M \sum_{L_n=1}^N \delta_{(O_i, O_j; L_m, L_n)}^\alpha \quad (1)$$

In Eq. (1), $\delta_{(O_i, O_j; L_m, L_n)}^\alpha = 1$ if the correlation of variable-A at grid (O_i, O_j) with variable-B at grid (L_m, L_n) exceeds the statistical significance level α , and $\delta_{(O_i, O_j; L_m, L_n)}^\alpha = 0$ if the correlation is not significant. M and N are the zonal and meridional grid numbers of variable-B, respectively. Here, the significance level (α) is chosen to be 95% based on a T-test.

For instance, if $BC_{(O_i, O_j)} = 9$ at an ocean grid (O_i, O_j), it means that precipitation anomaly at 9% of total land grid points has statistically significant (either positive or negative) correlations (at 95% significant level) with the SSTA at the ocean grid point. At the significance level of 95%, only the ocean grid point with $BC_{(O_i, O_j)} > 5$ (%) means that SSTA at the grid point may have a statistically significant connection with land precipitation anomaly over some regions. $BC_{(O_i, O_j)} \leq 5$ means that SSTA at the ocean grid point (O_i, O_j) does not have a significant connection with

global land precipitation anomaly. Through the spatial distribution of $BC_{(O_i, O_j)}$ in the observations and AMIP simulations, we can identify the key regions where SSTA may potentially have a significant impact on land precipitation anomaly in some regions, implying the oceanic source of land precipitation predictability.

3. Bulk Connectivity in the Observations

Figure 1 shows the spatial distribution of BC over the global ocean for each month. Statistically, the values larger than 5 correspond to the significance at the level of 95%, which are displayed in warm colors. It can be seen that large values of BC are mostly present in the tropical oceans with a maximum in the central and eastern Pacific and a secondary maximum in the Indian Ocean. The values in the subtropical Pacific, Indian, and Atlantic Oceans are also noticeable during certain months, such as September-December. Compared with those in the tropical Pacific and Indian Oceans, the BC values in the tropical Atlantic Ocean, as well as in the middle and high latitudes, are relatively smaller and less significant. The spatial distribution of BC suggests that global land precipitation variability as a whole has the strongest connection with the SSTAs in the tropical central and eastern Pacific and a moderate connection with the SSTAs in the tropical Indian Ocean. The results are similar when the precipitation anomaly lags SSTA by a couple of months (not shown), which is consistent with Wang and Fu (2000).

In addition to the spatial variation, the seasonal evolution of the connection between global land precipitation and SST variations is also pronounced (Fig. 1). An unexpected result is that the strongest connection occurs in October (Fig. 1j) while the weakest connection is seen in June (Fig. 1f). As it has been known, an ENSO cycle initiates in boreal spring and peaks in boreal winter. If ENSO was the sole determinant of the land precipitation anomaly, the maximum (minimum) BCs

would be in boreal winter and minimum BCs in boreal spring corresponding to the ENSO cycle (Hu et al. 2019b). The seasonal evolution of BC may be associated with both the ENSO cycle and the difference of the land areas between the two hemispheres. Given that ENSO SSTs likely have stronger influences on boreal winter precipitation anomaly than on boreal summer precipitation anomaly, and that the northern hemisphere has larger land areas than the southern hemisphere, it is reasonable to see a small BC in boreal summer (e.g., June, Fig. 1f). During December-February (DJF), strong and significant correlations of ENSO SSTA with precipitation anomaly are mainly over the northern hemisphere land (Fig. 8a), whereas in October, significant correlations are in both hemispheres over more land grid points (e.g., Fig. 8d), leading to large BC values. Thus, the seasonal evolution of the connection of SSTA with global land precipitation anomaly shown in Fig. 1 (the strongest in October and the weakest in June) is determined by both the seasonal variation of the impact of the tropical central and eastern Pacific SSTA and the difference of the land areas between the two hemispheres. The ENSO influences land precipitation anomaly through teleconnection, which not only relies on ENSO SSTA, but also depends on the background mean flow (e.g., Ting and Sardeshmukh 1993) that changes seasonally.

The seasonal evolution of the connection is more visible in the 2°S-2°N average (Fig. 2). In addition to the equatorial Pacific, a strong seasonal evolution also occurs along the equatorial Indian Ocean where the strongest connection appears in the western and central basin in September-November while the second-largest connection presents in the east in DJF. The weakest connection occurs in boreal summer (June-August) throughout the basin. Along the equatorial Atlantic Ocean, weak but statistically significant BCs (with values larger than 5 and warm color) are seen in March-October. Such different seasonal evolutions of the connections among the three ocean basins may be partially due to the inter-basin lead-lag connections (Wang et al. 2013; Cai

et al. 2019; Wang 2019). For example, the lagged impact of ENSO on the Indian and Atlantic Oceans (Kug et al. 2006; He et al. 2020; and references therein), as well as the persistence of the SSTA in the tropical oceans may lead to the spatial coherence of BCs shown in Figs. 1 and 2. Therefore, the tropical Indian and Atlantic Oceans may also have contributions to the seasonality of BC.

To check the robustness of the results, we repeat the calculations shown in Figs. 1 and 2 with the PRECP (Chen et al. 2002) and the ERSSTv5 (Huang et al. 2017) and get similar results (not shown). It is concluded that SSTAs in the tropical central and eastern Pacific exert the strongest influence on the land precipitation anomaly globally in October and have the weakest impact in June.

4. Bulk Connectivity in the AMIP Simulations

4.1 A single member

Do the connections shown in Figs. 1 and 2 represent the integrated impact of SSTA on land precipitation anomaly as a whole? If that is true, then such connections reflect the potential predictability of the land precipitation variability, since SSTA in the tropical oceans, especially in the tropical central and eastern Pacific associated with ENSO, is largely predictable at seasonal-interannual time scales (e.g., Xue et al. 2013; Zheng et al. 2016; Hue et al. 2019b). Such a hypothesis can be verified by comparing the similarity of the connections of the global land precipitation anomaly as a whole with SSTA between AMIP simulations and the observations. In AMIP simulations, precipitation variability includes the variability of the internal variability in the model and the response of the model to the observed SST specified in the AMIP integrations. The similarity of the connections between the observations and the AMIP runs implies that

precipitation variability in some land regions is driven by SSTA in some oceanic regions which are the sources of predictability for the land precipitation anomaly.

Figures 3 and 4 show the corresponding BC spatial and seasonal distributions as those shown in Figs. 1 and 2 respectively, except for an arbitrary choice member of the AMIP simulation. One ensemble member instead of the ensemble mean is adopted here to imitate the observations which include both the response to SST forcing and atmospheric dynamics driven variability. In general, the spatial BC distribution of the AMIP simulation (Fig. 3) is similar to the corresponding observations (Figs. 1), with the largest values mostly in the tropical central and eastern Pacific and moderate values in the tropical Indian Ocean. On the other hand, there are some noticeable differences in the seasonal evolution. For example, the 2°S-2°N average shows that the strongest connection occurs in October in the observation (Fig. 2) but in March and October in the AMIP simulation (Fig. 4).

For the global averaged BCs (Fig. 5), the maximum occurs in October in the observation (blue bars) and the values are comparable during October-March in a single-member AMIP simulation (green bar). The seasonality of the globally averaged BC from the AMIP run is generally smaller compared with the observations. Interestingly, for the global average, the amplitude of BC is systematically larger in the observation than in a single-member of AMIP simulations (blue and green bars, Fig. 5). This implies an underestimate of the influence of global SSTA on land precipitation variability as a whole in the model. This may reflect the fact that the AMIP simulations contain either a higher level of the atmospheric internal variability than the observations or weaker signals of forced precipitation anomaly over land by the SSTAs. In either case, the model signal-to-noise ratio (SNR) in a single-member of the AMIP simulation is lower than that in the observations.

4.2 Ensemble mean of 17- members

Figures 6 and 7 show the spatial and seasonal distributions of BC as those in Figs. 3 and 4 respectively, except for that the BC is calculated using the 17-member ensemble mean of the monthly mean precipitation anomaly from the AMIP simulations. Compared with the results of a single-ensemble member (Figs. 3, 4), the spatial distribution pattern of the ensemble mean BC is similar, while its amplitudes increase obviously. The global averaged BC shows a larger amplitude than those from both the observations and the one-member AMIP run. Moreover, there are differences in their seasonal evolution (Fig. 5). For instance, the maximum appears in October in observation (BC=8.3%), in March and October in a single-member of the AMIP simulations (5.9%), and in February in the ensemble mean of 17 members of the AMIP simulations (12.2%). It is also interesting to see that the ensemble mean BC shows a clear local maximum in October. The minimum is seen in June for both the observation (BC=5.7%) and the ensemble mean of 17 members of the AMIP simulations (6.5%) while it appears in April for the one member of the AMIP simulations (5.0%).

In addition to biases in the AMIP model, such differences may reflect the different features of the connection between the AMIP simulations and the observations. For example, the connections in the AMIP simulations (Figs. 3, 4, 6, and 7) reflect the response of the atmosphere (precipitation) anomaly to SSTA, while the connections in the observations represent a two-way interaction between the atmosphere and ocean. Moreover, climate prediction skill is linked to predictability and the SNR (e.g., Kumar and Hoerling, 2000; Kumar et al. 2001; Scaife and Smith 2018). As expected, the multi-member ensemble mean in the AMIP simulations suppresses SST-unrelated noise, i.e., the internal variability, and consequently elevates the SNR. Hu et al. (2020a)

noted that the correlation between observations and AMIP simulations is noticeably increased with the increase of ensemble size from 1 to 10. However, because the ensemble mean drastically reduces variability through the cancellation of the atmospheric dynamics driven internal variability, the ensemble mean is unlikely to be useful for predicting the strong/extreme variations of land precipitation.

5. Summary and Discussion

In this work, the connections between the global SSTA and the anomalous precipitation over land as a whole are assessed using observations and a set of the AMIP simulations for 1957-2018. To quantify the integrated connection of the SSTA at a given location with global land precipitation anomaly, the bulk connectivity (BC) metric is used. BC is defined as the percentage of the accumulated number of land grids, for which the correlation between the SSTA and land precipitation anomalies in each month reaches 95% significance level, to the total number of land grids. An advantage of this matrix is that at a grid point and a specified significance level, BC value is independent to the spatial resolution of the data used to do the calculations, since BC value denotes a percentage of the grid numbers reaching the significance to total grid numbers. Thus, the values of BC for the connectivity between two given variables can be quantitatively compared for different datasets in observations and/or model simulations. Furthermore, this matrix can be applied to any two variables in measuring their statistical bulk connection. The results with this matrix in this work can also serve as a benchmark to evaluate the connection of SSTA with global land precipitation anomaly in climate models.

Analyzing the spatial distributions and seasonal evolution of BC, the regions of SSTA having the most significant connection with global land precipitation anomaly as a whole are

identified and the seasonal evolution of the connection is evaluated. The similarities and differences of the BC characteristics between the observations and the AMIP simulations are further examined. In observations, the SSTAs in the tropical central and eastern Pacific connect most strongly with the global land precipitation anomaly. The connections with SSTA along the equatorial Indian and Atlantic Oceans are relatively weaker. In both the equatorial Pacific and Atlantic Oceans, BCs are enhanced roughly in the seasons of high SSTA standard deviation. Similar to the observations, both the single-member AMIP simulation and the ensemble mean of 17-member AMIP simulations have the strongest connection of global land precipitation anomaly as a whole with SSTA in the tropical central and eastern Pacific. However, the integrated global connection shows different seasonal evolution patterns in the observations, the single-member AMP simulation, and the 17-member ensemble mean of the AMIP simulations. The strongest (weakest) connections are in October (June) in the observation, in March and October (April) in one member of the AMIP simulation, and in February (June) in the 17-member ensemble mean of the AMIP simulations. In general, ensemble averaging substantially improves the BC magnitude and seasonality. In particular, it shifts the minimum of the globally averaged BC from April in the single-member simulation to June as observed. It also significantly enhances the BC in October to a clear local maximum, consistent with the observations.

A plausible reason for the BC differences between the AMIP simulations and observations is that the ensemble mean of the AMIP simulations reflects the atmospheric response to SST, while the observations include both the atmospheric response to SSTA and internal variability driven by the internal dynamics. It has been demonstrated that the two-way interaction plays a key role in the summer climate variability in the western North Pacific (Wu and Kirtman, 2005; Wang et al. 2005; Zhu and Shukla 2013). Without the atmosphere-ocean coupling, the variability of the

western Pacific subtropical high is not well simulated, which leads to a failure of reproducing the summer climate (rainfall) variability in the region. Undoubtedly, the lack of feedback from the atmosphere to the ocean in the AMIP simulation is a potential factor deforming and weakening the connection between SST and land precipitation variations in some regions, leading to some of the differences between the AMIP simulations and observations. Therefore, the AMIP approach may have its limitation and the BC distributions should be further evaluated in fully coupled simulations.

From Figs. 1-4, we note that the maximum values of BC appear in the tropical central and eastern Pacific Ocean approximately in the Niño3.4 region (5°S-5°N, 170°-120°W; Barnston et al. 1997). Based on the results in Figs. 1-4, we calculate the simultaneous correlations of global SST and land precipitation anomalies with SSTA indices averaged in the tropical central and eastern Pacific (see the rectangles in Fig. 8). The regions for the averaged SSTA indices are shifted slightly in the zonal direction with the month to fit the seasonal changes in the major BC area. The correlation with SSTA shows a pattern similar to the connection of global SSTA with ENSO, although the correlation amplitudes vary monthly. For the connection with global land precipitation anomaly, there are profound differences in various months for the regions with significant correlations. Take Australia as an example: there are no significant correlations there in April and June (Fig. 8b, c), a few significant correlation regions in January (Fig. 8a), but plentiful significant correlations in October (Fig. 8d). These results are consistent with the seasonality of the BC shown in Figs. 1, 2, and 5.

Nevertheless, we must point out that for seasonal-interannual climate variability in the extratropical land regions, the internal dynamical processes linked to unpredictable components play a dominant role. As an example, the relationship of ENSO with the forecast skill of the

Climate Prediction Center (CPC) for seasonal mean precipitation and temperature anomalies over the U. S. is displayed (Fig. 9). The official forecasts are expressed in 3 categories: above normal, near normal, and below normal, and span January 1995-December 2019. The forecast skill is measured by the Heidke Skill Score, which compares how often the forecast category correctly matches the observed category, over or above the number of correct "hits" expected by random chance alone (O'Lenic et al. 2008; Peng et al. 2013). The skill score values range from -50 to 100 with a score of 100 (-50) meaning a perfect correct (incorrect) forecast. A score value greater than 0 indicates a skillful forecast compared to a random forecast. In the CPC official seasonal forecasts, ENSO is the most important predictor (O'Lenic et al. 2008; Peng et al. 2013). From the scatter plot, ENSO's role is visible. For instance, the skill scores for seasonal temperature forecasts are positive and relatively large when Niño3.4 index $\geq 2.0^{\circ}\text{C}$ (Fig. 9b). Meanwhile, we also see a pronounced spread of the skill scores within different phases of ENSO. During La Niñas (Niño3.4 index $\leq -0.5^{\circ}\text{C}$; green triangles), both negative and positive scores for the precipitation and temperature anomaly forecasts are present. That further illustrates the challenge and limitation of the seasonal forecast in the extratropical land regions, even if in the regions significantly affected by ENSO, such as the U. S.

The matrix of BC used in this work relies on correlation coefficients between two variables. The interannual variations in monthly precipitation mostly have normal distribution under a humid climate to some extent. However, they may not have normal distribution under an arid climate where heavy rainfall occurs as a rare event with a long return-period. Thus, the correlation coefficient might not correctly reflect the connectivity. Moreover, the gridded precipitation data was partially derived from the interpolation of observation from rain gauges. The precipitation variation with a coarse network of observation over the northern and inland regions of Eurasia may

affect the results to some extent. Lastly, whether the results are model dependence may be verified by analyzing AMIP runs from other models.

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Fig. 1: BC in the observations: percentage of accumulated grid numbers for the correlation between observed SSTA at a grid and global precipitation anomaly in each month which reaches a 95% significance level using a T-test, referred to total grid number of global land precipitation during January 1957-December 2018. The significance areas are displayed in warm color with values equal to or larger than 5 (%).

Fig. 2: Same as Fig. 1, but for 2°S–2°N average. The contours show the SSTA standard deviation stratified by calendar months (contour interval 0.2°C).

Fig. 3: BC in one member of the AMIP simulation. The significance areas are displayed in warm color with values equal to or larger than 5 (%).

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568 Fig. 4: Same as Fig. 3, but for 2°S–2°N average.

Global Mean of % of Global Land Grid Having 95% Significant Correlation With SST
Blue: Observation; Green: AMIP; Red: Ensemble; Line: 5% (1957–2018; 10YR HP)

Fig. 5: Global averaged BC. The blue bars represent the observations; green bars are one AMIP run; red bars denote the ensemble mean of 17 AMIP runs; zonal dash line is referred to as a 95% significance level of a T-test.

Fig. 6: Same as Fig. 3, but for BC of the ensemble mean of 17 members.

Fig. 7: Same as Fig. 4, but for BC of the ensemble mean of 17 members.

Fig. 8: Simultaneous correlations of observed SSTA and land precipitation anomalies with tropical Pacific SSTA indices averaged (a) in (5°S–5°N, 180°–110°W) in January, (b) in (5°S–5°N, 180°–120°W) in April, (c) in (5°S–5°N, 180°–120°W) in June, and (d) in (5°S–5°N, 180°–110°W) in October during 1957–2018. The SSTA averaged regions (rectangles) are chosen based on Figs. 1–6, to represent the months and tropical Pacific regions having relatively maximum or minimum correlations between SSTA and precipitation anomalies. Hatching (dot) denotes significant correlations of SSTA (precipitation anomaly) at the significance level of 95% using a T-test. The left color bar represents the correlation of the SSTA indices with the precipitation anomaly over land, and the right color bar is for the correlation of the SSTA indices with SSTA.

Fig. 9: Scatter plots of observed seasonal mean Niño3.4 index (x-axis) and Heidke Skill Score of CPC official seasonal forecast (y-axis) of (a) precipitation and (b) temperature anomalies over U. S. during 1995-2019. The green triangles, black dots, and red squares represent seasonal mean Niño3.4 index $\leq -0.5^{\circ}\text{C}$, between -0.5°C and 0.5°C , and $\geq 0.5^{\circ}\text{C}$, respectively. The horizontal blue dashed lines represent the averaged skill scores.

Figures

Figure 1

BC in the observations: percentage of accumulated grid numbers for the correlation between observed SSTA at a grid and global precipitation anomaly in each month which reaches a 95% significance level using a T-test, referred to total grid number of global land precipitation during January 1957-December 2018. The significance areas are displayed in warm color with values equal to or larger than 5 (%). Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

Figure 2

Same as Fig. 1, but for 2oS–2oN average. The contours show the SSTA standard deviation stratified by calendar months (contour interval 0.2oC). Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

Figure 3

BC in one member of the AMIP simulation. The significance areas are displayed in warm color with values equal to or larger than 5 (%). Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

Figure 4

Same as Fig. 3, but for 2oS–2oN average. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

Figure 5

Global averaged BC. The blue bars represent the observations; green bars are one AMIP run; red bars denote the ensemble mean of 17 AMIP runs; zonal dash line is referred to as a 95% significance level of a T-test.

Figure 6

Same as Fig. 3, but for BC of the ensemble mean of 17 members. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

Figure 7

Same as Fig. 4, but for BC of the ensemble mean of 17 members. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

Figure 8

Simultaneous correlations of observed SST and land precipitation anomalies with tropical Pacific SSTA indices averaged (a) in (5oS–5oN, 180o–110oW) in January, (b) in (5oS–5oN, 180o–120oW) in April, (c) in (5oS–5oN, 180o–120oW) in June, and (d) in (5oS–5oN, 180o–110oW) in October during 1957–2018. The SSTA averaged regions (rectangles) are chosen based on Figs. 1–6, to represent the months and tropical Pacific regions having relatively maximum or minimum correlations between SST and precipitation anomalies. Hatching (dot) denotes significant correlations of SSTA (precipitation anomaly) at the significance level of 95% using a T-test. The left color bar represents the correlation of the SSTA indices with the precipitation anomaly over land, and the right color bar is for the correlation of the SSTA indices with SSTA. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

Figure 9

Scatter plots of observed seasonal mean Niño3.4 index (x-axis) and Heidke Skill Score of CPC official seasonal forecast (y-axis) of (a) precipitation and (b) temperature anomalies over U. S. during 1995-2019. The green triangles, black dots, and red squares represent seasonal mean Niño3.4 index $\leq -0.5^{\circ}\text{C}$, between -0.5°C and 0.5°C , and $\geq 0.5^{\circ}\text{C}$, respectively. The horizontal blue dashed lines represent the averaged skill scores.