Understanding Prediction Skill of Seasonal Mean Precipitation over the Tropics

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(Manuscript received 8 October 2012, in final form 13 February 2013)

ABSTRACT

The connection between the local SST and precipitation (SST–P) correlation and the prediction skill of precipitation on a seasonal time scale is investigated based on seasonal hindcasts from the National Centers for Environmental Prediction (NCEP) Climate Forecast System version 2 (CFSv2). The results demonstrate that there is good correspondence between the two: precipitation skill is generally high only over the regions where SST–P correlation is positive and is low where SST–P correlation is small or weakly negative. This result has fundamental implications for understanding the limits of precipitation predictability on seasonal time scale and helps explain spatial variations in the skill of seasonal mean precipitation. Over the regions where atmospheric variability drives the ocean variability (and consequently the local SST–P correlation is weakly negative), the inherently unpredictable nature of atmospheric variability leads to low predictability for seasonal precipitation. On the other hand, over the regions where slow time scale ocean variability drives the atmosphere (and the local SST–P correlation is large positive), the predictability of seasonal mean precipitation is also high.

1. Introduction

It has been demonstrated that the simultaneous correlation between observed sea surface temperature and precipitation (SST–P) on monthly and seasonal time scales has a widely ranging geographical variation (e.g., Arakawa and Kitoh 2004; Trenberth and Shea 2005; Chen et al. 2012). The SST–P correlation is highly positive over the tropical Pacific, the core region of interannual variability associated with El Niño–Southern Oscillation (ENSO). Over other tropical ocean basins, the SST–P correlation is either only weakly positive or, even at some locations, is found to be weakly negative. These features are substantiated in Fig. 1, where the spatial pattern of SST–P correlation for different seasons is shown based on observed seasonal mean SST and precipitation anomalies over the 1982–2010 period.

Reasons for geographical variations in the SST–P relationships can be understood within the context of ocean–atmosphere coupled evolution and whether ocean is the driving mechanism for the precipitation (and atmospheric) variability or vice versa. Ocean driving the atmosphere or atmosphere driving the ocean, coupled with the typical time scale associated with the respective mechanism, provides a conceptual framework for understanding the geographical variations in the SST–P correlation and its amplitude, and this framework is summarized in Fig. 2.

In tropical latitudes, a fundamental tenet of precipitation variability is its influence on the heat flux at the ocean surface due to changes in cloudiness and its influence on downward solar radiation. An increase (decrease) in precipitation results in a decrease (increase) in downward solar radiation at the ocean surface, which in turn tends to decrease (increase) local SSTs. This conceptual picture leads to the expectation that the correlation between local SST and precipitation variability will tend to be negative and, over the tropical oceanic regions where SST is controlled by atmospheric variability, negative SST–P correlations will occur. Such oceanic regions are often referred to as the regions where the atmospheric variability drives the oceanic variability (Fig. 2, middle). Further, as the atmospheric variability decorrelates on a fast time scale (and a coherent long-lasting precipitation forcing for the ocean cannot be sustained), negative SST–P correlations tend to be weak. We should point out that the mechanism for precipitation variability on the underlying SST variability outlined above is a very simplistic view and can be
augmented by changes in the other surface flux components: for example, latent heat flux.

At some locations in tropical Pacific, the out of phase relationship between precipitation and SST variability is overcome by the influence of ocean dynamics and coupled air–sea interactions on the SST variability. An example of this is the SST variability in the tropical central Pacific associated with ENSO where long-lasting SST anomalies are sustained by oceanic adjustment processes and coupled air–sea feedback. These long-lasting SST anomalies also force in phase precipitation variability. During El Niño (La Niña) events, the mean SST in tropical central Pacific goes above (below) the threshold of $\pm 28^\circ C$ that is necessary for sustaining convection (Gadgil et al. 1984; Zhang 1993); thence, El Niño (La Niña) events with warm (cool) SST anomalies are also accompanied by higher (lower) precipitation, leading to positive SST–P correlations. Such oceanic regions are referred to as the regions where ocean variability drives the atmosphere (Fig. 2, left), and further, as the time scale of ocean variability tends to be longer, positive SST–P correlations also tend to be stronger than their negative counterpart. We should point out that, even though the local heat flux associated with the precipitation variability still acts as a negative feedback to dampen the SST anomaly (Kumar and Hu 2012), this feedback is overcome by the control of ocean dynamics on SSTs.

For the regions where precipitation variability controls the SST variability, there is also a subclass for which precipitation variability is teleconnected to slow oceanic variability over a remote region via the atmospheric bridge mechanism (Klein et al. 1999; Alexander et al. 2002). These oceanic regions, where SST–P is also negative, have a special significance and are shown in Fig. 2 (right).

The conceptual framework for the geographical variation in the SST–P correlation discussed above also has implication for predictability, as well as prediction skill, of precipitation on monthly and seasonal time scales. Over the regions associated with the left panel in Fig. 2, one might expect higher prediction skill (and predictability) for precipitation as the slow ocean, and SST variations are in control of the interannual variations in precipitation. Over the regions associated with the middle panel in Fig. 2 where precipitation variability is associated with fast atmospheric variations and negative SST–P correlations occur, because of inherently unpredictable nature of atmospheric variability, prediction skill (and predictability) of precipitation will also be low. Following this, in the assessment of precipitation skill in monthly and seasonal prediction systems, regions of high (low) precipitation prediction skill should tend to coincide with the regions of high (low) SST–P correlations. If this is indeed the case, it then provides a physical understanding for spatial variations for the skill of time mean precipitation. The spatial correspondence between SST–P correlation and skill of precipitation is investigated based on the Climate Forecast System version 2 (CFSv2) that is operational at the National Centers for Environmental Prediction (NCEP). The data and a brief description of CFSv2 are given in section 2; results are presented in section 3; and concluding remarks are presented in section 4.

2. Data and analysis method

The model forecast data analyzed in the study are hindcasts from the NCEP CFSv2. CFSv2 is a fully coupled dynamical prediction system. The atmospheric component of the CFSv2 is a 2007 version of the NCEP Global Forecast System (GFS) (Saha et al. 2010), with a spectral truncation of 126 waves (T126) in the horizontal
(equivalent to nearly a 100-km spatial resolution) and 64 layers in vertical. The oceanic component is the Geophysical Fluid Dynamics Laboratory Modular Ocean Model version 4 (MOM4) (Griffies et al. 2004). In CFSv2 the configuration of the MOM4 has 40 levels in the vertical, a zonal resolution of $\frac{1}{2}^\circ$, and a meridional resolution of $\frac{1}{8}^\circ$ between $10^\circ S$ to $10^\circ N$ that gradually increases through the tropics until becoming fixed at $\frac{1}{2}^\circ$ poleward of $30^\circ S$ and $30^\circ N$. CFSv2 forecasts are initialized from the NCEP Climate Forecast System Reanalysis (CFSR) (Saha et al. 2010) atmospheric and ocean states. The CFSv2 has shown reasonable forecast skills for seasonal mean SST and other variables: largest skill for SST and precipitation in the equatorial central Pacific and larger skill during boreal winter than during summer (Kim et al. 2012a,b; Kumar et al. 2012).

For CFSv2 seasonal hindcasts, four forecast runs were made every 5 days starting 1 January without considering 29 February in leap years. Each forecast run covers the rest of the beginning month after the initial date and nine following target months. In this study, the hindcast data from 1982 to 2010 are organized with respect to the target season with 20 forecast members starting from the month before the target season: the December–February (DJF) forecast includes 20 members from initial conditions of 7, 12, 17, 22, and 27 November with four runs at each initial day; the March–May (MAM) forecast is from initial conditions of 5, 10, 15, 20, and 25 February; the June–August (JJA) forecast is from initial conditions of 11, 16, 21, 26, and 31 May; and the September–November (SON) forecast is from initial conditions of 9, 14, 19, 24, and 29 August.

In our analysis, the precipitation skill is defined as anomaly correlation coefficient (ACC) between CFSv2 ensemble mean of 20 members and corresponding observation from the Climate Prediction Center (CPC) Climate Anomaly Monitoring System outgoing longwave radiation precipitation index (CAMS-OPI) (Janowiak and Xie 1999). The SST–P correlations in CFSv2 are calculated from each individual forecast member, and then the correlations are averaged for all 20 members.

The reason for using ensemble mean for computing precipitation skill is because the forecast based on the ensemble mean leads to larger prediction skill (Kumar and Hoerling 2000). On the other hand, SST–P correlations are computed based on individual forecasts to compare them against their observational counterpart. In the context of this analysis, we note that the choice of a 20-member ensemble is somewhat arbitrary. For the SST–P correlation analysis, as correlations are done for individual forecast members and are subsequently averaged for comparison against their observational counterpart (which is equivalent to a single forecast member), the average of 20 correlations does provide a stable estimate of SST–P relationship for model forecasts. For the computation of precipitation skill, Kumar...
and Hoerling (2000) analyzed variation in skill with ensemble size and reported that an ensemble size of \(\sim 15\) is adequate to provide an accurate estimate of true prediction skill. This is even truer for tropical latitudes (the focus of our analysis) where signal to noise in precipitation variability due to SST variability (which is the main source of prediction skill for seasonal means) is higher (Peng et al. 2000).

The SST observation used in calculation of the observed SST–\(P\) correlation (Fig. 1) is from Reynolds et al. (2002) and the precipitation observation is from CAMS-OPI (Janowiak and Xie 1999). All calculations in the study are based on 3-month-running seasonal anomalies relative to 1982–2010 climatology.

3. Results

a. Local SST–\(P\) correlations

The focus of the paper is to investigate possible correspondence between local SST–\(P\) correlation and prediction skill of precipitation. For observations local SST–\(P\) correlation for four cardinal seasons is shown in Fig. 1. The SST–\(P\) correlation has its maximum over the tropical eastern Pacific, a region coinciding with largest interannual variability in SSTs related to ENSO (Wang et al. 2005; Kumar et al. 2010). Over other regions, SST–\(P\) correlations are either weakly positive or weakly negative. An interesting region is the east tropical Indian Ocean near the Maritime Continent, where SST–\(P\) correlations have a strong seasonality with large positive correlation during JJA and SON and negative correlation in DJF and MAM. This region coincides with the eastern pole of the Indian Ocean dipole mode (IODM) variability and change in the sign of SST–\(P\) correlations is indicative of a regime shift from ocean variability forcing the atmosphere to vice versa (Chen et al. 2012). We also note that the range of positive SST–\(P\) correlation is much larger than their negative counterpart and is consistent with the notion (and discussion in section 1) that positive SST–\(P\) correlations are due to slow (and often predictable) changes in SST driving atmospheric variability, while negative correlations are due to fast (unpredictable) atmospheric changes imparting their fingerprint on ocean evolution.

To examine how well the coupled model forecast replicate the observed SST–\(P\) relationship, spatial distributions of the local simultaneous correlation between seasonal mean anomalies of precipitation and SST for CFSv2 hindcast are shown in Fig. 3. Similar to Fig. 1 for observations, the CFSv2 SST–\(P\) correlations are also shown for four seasons. For CFSv2 as the SST variability is forecasted internally, SST–\(P\) correlations are also a consequence of a self-consistent SST–\(P\) relationship.

There are strong similarities in the spatial distribution of SST–\(P\) correlation between CFSv2 and observations. The SST–\(P\) correlations, in both observation and CFSv2, have the largest positive correlations over the tropical eastern Pacific. However, CFSv2 shows a larger extent of positive SST–\(P\) correlations: for example, over the northwest Pacific (DJF and MAM), southern Indian Ocean (JJA and SON), and northern and southern subtropical areas of Atlantic Ocean. Reasons for this are not clear and will be pursued in future analysis. Over the Maritime Continent to the eastern tropical Indian Ocean, CFSv2 also has a reversal in the sign of SST–\(P\) correlation and follows the same seasonality as in observations. Finally, similar to observations, the range of positive SST–\(P\) correlation is much larger than for the negative SST–\(P\) correlation.

The implications of spatial variability in SST–\(P\) correlations have been extensively discussed in relation of the setup of model integrations, particularly in the context of uncoupled and coupled model integrations.
(Kumar and Hoerling 1998; Wu et al. 2006; Chen et al. 2012). For example, in model simulations where the evolution of SSTs is specified externally [the so-called Atmospheric Model Intercomparison Project (AMIP) simulations], the atmospheric (and associated precipitation) variability does not feedback on the evolution of SSTs. As a consequence, negative SST–P correlations cannot be simulated. On the other hand, AMIP simulations can well reproduce positive SST–P correlations in regions over which the specified SST controls the precipitation variability (Peng et al. 2000; Chen et al. 2012).

b. Seasonal mean prediction skill of precipitation

As discussed earlier, a positive SST–P correlation is consistent with the notion of forcing of atmospheric variability by the underlying SSTs (the time scale of which is governed by slow oceanic processes), and if this is the case then correct prediction of SST in CFSv2 forecasts should also lead to a skillful precipitation forecast. On the other hand, a negative SST–P correlation implies the atmosphere controls the SST evolution and, since the atmospheric variability is unpredictable for longer lead forecasts (e.g., beyond couple of weeks), one would expect a low skill of precipitation prediction. This reasoning argues for a correspondence between the spatial structure of SST–P correlation and prediction skill of precipitation and has the potential for providing an explanation for spatial variability for the latter. To examine whether this is indeed the case, we next analyze the skill of seasonal mean precipitation for the CFSv2 and its relationship with the observed SST–P correlation.

Figure 4 shows the seasonal mean precipitation forecast skill from CFSv2 for four seasons. By comparing Fig. 4 with Fig. 1, high (low) skill for precipitation is generally collocated with positive (low or negative) SST–P correlation, although there are some areas where the high precipitation skill corresponds to low or negative SST–P correlation. This relationship can be seen better in Fig. 5, where a scatterplot between the observed SST–P correlation and precipitation skill for four seasons is shown. In Fig. 5, the relationship in precipitation skill with SST–P correlation can be classified into three broad regimes as described in the conceptual framework of Fig. 2.

In regime I (Fig. 2a), the tendency for large positive SST–P correlations collocated with large precipitation skill is evident from the top-right quadrant for which large positive SST–P correlations also accompany large precipitation skill. Such a collocation is consistent with the notion that (i) control of local SSTs on precipitation variability and (ii) the evolution of SSTs themselves are due to slow oceanic processes and can be predicted on seasonal time scale. In regime II (Fig. 2b), the tendency for low/negative SST–P correlations to be collocated with low precipitation skill falls in the bottom-left quadrant. For this regime, unpredictable atmospheric variability leads to both small precipitation skill and weak SST–P correlations.

In regime III (Fig. 2c), the low/negative SST–P correlations collocated with intermediate, positive values of precipitation skill are in the top-left quadrant. The most evident areas of this regime include the northeast subtropical Pacific and west of the Maritime Continent in the Indian Ocean (DJF and MAM); these are regions that have strong teleconnection with ENSO variability (Chen et al. 2012). Over these regions, precipitation is forced remotely by slow variation in the tropical Pacific SST and therefore has good prediction skill while at the same time can affect local SST evolution and, in the paradigm of precipitation variations forcing the ocean, results in negative SST–P correlation. The possibility of connection with ENSO variability is further indicated by
the preponderance of number of points with negative SST–P correlation but high precipitation skill during DJF and MAM, when ENSO SST anomalies are at their peak (followed by the decay phase) and the teleconnection patterns are best defined (Trenberth et al. 1998; Kumar and Hoerling 2003).

To confirm that regime III is indeed associated with regions of ENSO teleconnection in precipitation response, in Fig. 6 the regression pattern between the observed Niño-3.4 SST index and precipitation is shown. For discussion, we focus on DJF and MAM and highlight the regions over which precipitation skill is high while the SST–P correlation is negative. As indicated before, these regions are over the northeast subtropical Pacific and west of the Maritime Continent in the Indian Ocean. As the regression map (Fig. 6) indicates, over these regions precipitation is indeed related to the remote ENSO variability.

The notion of three regimes categorizing the inter-relationship between the SST–P correlation and skill of seasonal mean precipitation in terms of different physical process is a broad categorization and cannot account for the full complexity of physical processes that occur over the oceanic regions. Indeed, the correlation between SST–P correlation and precipitation skill for various seasons ranges from 0.65 (MAM) to 0.81 (SON) and, although significant, does not account for the full spectrum of variability.
Apart from the complexity of physical processes that may further influence the correspondence between SST–P correlations and precipitation skill based on the notion of ocean forcing the atmosphere or vice versa, the possible interaction of both mechanisms acting at the same geographical location is another confounding factor. An example of this is over the western side of the Maritime Continent, the region collocated with the eastern pole of the IODM. This is a region over which, during JJA and SON, SST–P correlation is strongly positive (Fig. 1 for observations and Fig. 3 for CFSv2) and implies oceanic forcing for the precipitation (i.e., regime I); however, at the same time ENSO teleconnection is also strong (Fig. 6) and is out of phase for precipitation variability with the ENSO-associated SSTs. The latter is consistent with the concept of long-lasting atmospheric forcing for the ocean (as for the regime III). Even though both factors would lead to a good prediction skill (as is indeed the case; Fig. 4), the physical process of ocean forcing the atmosphere or vice versa is a superposition of two, with ocean forcing the atmosphere playing the dominant role.

4. Concluding remarks

A fundamental result of this study is demonstrating a correspondence between local SST and precipitation (SST–P) correlation and skill of precipitation on seasonal time scale. In general, precipitation skill is high over the regions where SST–P correlation is positive and low where SST–P correlation is either small or weakly negative. The physical basis why such a correspondence may exist was also discussed.

The results of this analysis have implications for understanding limits of precipitation predictability and spatial structure of precipitation skill on a seasonal time scale. For seasonal predictions, the regions where precipitation skill is small may not be due to model biases or initialization errors but due to atmospheric variability being the dominant controlling mechanism, which is the basic factor constraining skill of seasonal mean precipitation. The inherent unpredictability associated with atmospheric variability controlling precipitation, as well as the evolution of underlying SSTs, both determines low SST–P correlations and puts a fundamental limit on precipitation skill.

Acknowledgments. Thanks for Drs. Peitao Peng and Caihong Wen for CPC internal manuscript reviewing. Constructive comments by three anonymous reviewers led to improvements in the final version of the manuscript.

REFERENCE


