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Seasonal climate predictability with Tier-one and Tier-two prediction systems

Jong-Seong Kug · In-Sik Kang · Da-Hee Choi

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Abstract In this study seasonal predictability of Tier-one and Tier-two predictions are evaluated and compared. Through the comparison of these two predictions, it is demonstrated that the air–sea coupled process is an important factor not only for climatological simulation but also for seasonal predictability. In particular, the air–sea coupling plays a crucial role over the warm pool region, as the atmosphere tends to lead the ocean in anomalous variability. In this region, the Tier-one prediction has better climatology compared to the Tier-two prediction despite the presence of a climatological SST bias. Furthermore, the Tier-one has a relatively higher seasonal predictive skill than that of the Tier-two although its SST prediction skill is relatively poor. It is suggested that the air–sea coupled process plays a role to reduce both the climatological and anomalous biases in the uncoupled AGCM by means of the negative feedback of the SST-heat flux-precipitation loop. Using the CliPAS and DEMETER seasonal prediction data, the robustness of these results are demonstrated in the multi-model frame works.

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J.-S. Kug
Climate Environment System Research Center,
Seoul National University, Seoul, South Korea

I.-S. Kang (✉) · D.-H. Choi
School of Earth and Environmental Sciences,
Seoul National University, Seoul 151-742, South Korea
e-mail: kang@climate.snu.ac.kr

1 Introduction

As scientific and economic interests in seasonal climate prediction and predictability have increased considerably in recent years, many studies have been devoted to its implementation and improvement. So far, the dynamic seasonal prediction has been mainly carried out by Tier-two (T2) and Tier-one (T1) prediction systems in most operational centers. In the T2 system, the seasonal prediction is performed using only atmospheric GCM with the prescribed SST boundary condition, which is previously predicted by a coupled GCM or statistical model. The T2 is based on the notion that the seasonal mean anomalies are mainly resulted from SST changes and that seasonal atmospheric anomaly can be predictable by prescribed SST anomalies (Shukla 1998; Shukla et al. 2000). On the other hand, the T1 system uses a coupled GCM which contains an interacting physics between atmosphere and ocean. Therefore, the air–sea coupled process[1] can be considered in the T1 system. Though the two prediction systems are currently used for seasonal prediction, so far it has not been evaluated how much the air–sea coupled process is important in season predictability. In this study, seasonal predictability of the T2 and T1 predictions will be evaluated and compared using SNU (Seoul National University) T1 and T2 prediction systems, which share same atmospheric component model.

Though seasonal atmospheric anomaly is largely determined by seasonal SST anomaly, the uncoupled AGCM simulation like the T2 prediction has a systematic problem

[1] The terminology ''air–sea coupled process'' contains various physical processes between atmosphere and ocean, but it will be specified in this study as a feedback from atmosphere to ocean, which is not embedded in the T2 system unlike the T1 system.

due to the absence of feedback from the atmosphere to the ocean. Many intercomparison studies showed that most AGCMs have a difficulty in simulating the observed rainfall anomalies over the summer monsoon region (Gadgil and Sajani 1998; Kang et al. 2002; Wang et al. 2004). For example, Wang et al. (2004) compared the summer monsoon rainfall anomalies of 11 AGCMs during the 1997/1998 El Nino. Over south-east Asia and the western north Pacific (WNP), where air–sea interactions play an important role in the predictability of summer monsoon rainfall, the lack of skill in the simulation of rainfall anomalies has been attributed to the fact that AGCMs fail to produce accurate air–sea interactions. The observed monthly rainfall anomalies are negatively correlated with the monthly SST anomalies (Correlation coefficient is –0.35 over the Southeast Asia and the tropical WNP region), indicating that the SST anomalies are a response to atmospheric forcing in monthly to seasonal time scales. However, the reproduced rainfall anomalies in the AGCM are almost positively correlated with the SST anomalies. This suggests that the discrepancy occurs not from defects in the model physics but from the experimental design in which the atmosphere is forced to respond passively to the prescribed SST without considering the air–sea interaction.

Furthermore, Wang et al. (2005) also suggested the importance of air–sea coupled processes by comparing coupled and forced AGCMs. The predicted precipitation anomalies using only AGCMs over the ENSO region are well simulated to some extent, while most of the AGCMs have a difficulty in simulating the observed rainfall anomalies over the summer monsoon region. The likely cause for this difficulty is the lack of atmospheric feedback to the ocean over the WNP region, where the air–sea coupled processes play an important role in the predictability of summer monsoon rainfall. The observed summer mean SSTs and precipitation anomalies are negatively correlated in the WNP. However, the forced experiment model is unable to reproduce the observed negative SST–rainfall relationship, and instead reproduces a positive correlation. In contrast, the coupled experiment is able to simulate the observed relationship between the SST and rainfall. The summer monsoon rainfall cannot be correctly simulated by prescribing lower boundary forcing over the warm pool region because the SST anomalies cannot be interpreted as a forcing and are instead determined by the anomalous atmospheric conditions.

Recently, a few operational centers have begun seasonal climate prediction using the T1 prediction system, which includes the air–sea coupled process. Moreover, some noteworthy results of seasonal predictions in current CGCMs have been presented (Stockdale et al. 1998; Davey et al. 2002; Palmer et al. 2004). Additionally, the superiority of CGCMs over the simulations of AGCMs has been addressed in several studies (Kitoh and Arakawa 1999; Yu and Mechoso 1999; Fu et al. 2002; Wang et al. 2005; Graham et al. 2005). Fu et al. (2002) showed that air–sea coupling plays an important role in the climatological simulation of the Asian summer monsoon over the Indian Ocean and western Pacific region. Moreover, climatological intraseasonal oscillation (CISO), defined by Kang et al. (1999), is better simulated in CGCM than in the AGCM. Additionally, they have emphasized the possible impacts of air–sea coupling on the simulation of the summer monsoon by adjusting SST based on the errors in the atmospheric model.

Many studies indicate the superiority of CGCM simulation over AGCM simulation in simulating rainfall variability over the monsoon and warm pool regions. However, a comparison of Tier-one and Teir-two systems on real seasonal prediction has not yet been reported in detail. Additionally, the importance of the air–sea coupling in seasonal predictability is not sufficiently understood. The performance comparisons of the seasonal predictability will provide insights into the benefits of T1 CGCM systems over T2 AGCM systems. In this study, the seasonal predictability of the T2 and T1 predictions is evaluated and compared using the SNU T1 and T2 prediction systems, which share the same atmospheric component model. Since the same atmospheric component is used in both systems, the performance differences will be responsible for the impact of the air–sea coupling in the CGCM. Therefore, by comparing of both systems, we will demonstrate that the air–sea coupling is critical for both the seasonal predictability as well as for the climatological simulation. In particular, we will focus on summer (JJA) predictability over the warm pool where the air–sea coupling is most critical on the seasonal variability.

Section 2 describes the model description of the SNU T1 and T2 seasonal prediction systems. In Sect. 3, the climatological simulation is evaluated in the T1 and T2 systems, as is the importance of the air–sea coupled process in simulating climatological precipitation. Section 4 shows the seasonal predictability of the two systems, and the systematic biases in the two prediction systems. Using CliPAS and DEMETER seasonal prediction data, the T2 and T1 predictions of multi-models are compared in Sect. 5. A summary and discussion are given in Sect. 6.

2 Model descriptions and prediction designs

2.1 Model descriptions

The atmospheric model used in the current T2 prediction system is the SNU AGCM. This AGCM is a spectral model with a triangular truncation at wave number 63 and has 20 vertical levels. The physical processes included are the Nakajima two-stream scheme for longwave and shortwave radiation (Nakajima et al. 1995), the relaxed Arakawa-Schubert scheme (Moorthi and Suarez 1992), shallow convection, land surface processes, gravity wave drag, and planetary boundary layer processes (Kim et al. 1998). Kim et al. (1998) showed that the SNU GCM reasonably simulates the climatological mean patterns of tropical circulation and their anomalies during El Nino.

In the T2 prediction, the AGCM was forced by a predicted SST (Bengtsson et al. 1993). The present T2 prediction system uses the global SST prediction from the SNU dynamical and statistical ensemble prediction system (Kug et al. 2007). The SST prediction system consists of the dynamic El Nino prediction model (Kang and Kug 2000; Kug et al. 2001, 2005), lagged linear regression model (LLR, Kug et al. 2004), coupled pattern projection model (CPPM), and persistent SST. Using four SST predictions, the predicted SST anomalies are obtained by an ensemble procedure. The monthly SST anomalies are superposed to observed SST climatology, in order to be used for boundary condition of the T2 prediction. Details on the procedure of the SST prediction refer to Kug et al. (2007).

The CGCM used in the T1 prediction system was developed at Seoul National University. The atmospheric component is the same AGCM as the T2 system with T42 triangular truncation. We checked that two AGCMs, having different resolution of T42 and T63, have a similar performance to simulate climatology and interannual variability of atmospheric variables. The oceanic component is the MOM2.2 Oceanic GCM developed at the Geophysical Fluid Dynamic Laboratory (GFDL). The model is a finite difference treatment of the primitive equations of motion using the Boussinesq and hydrostatic approximations in spherical coordinates. The domain of the model covers most global oceans, and its coastline and bottom topography are realistic. The zonal resolution is 1.0°. The meridional grid spacing between 8°S and 8°N is 1/3°, gradually increasing to 3.0° at 30°S and 30°N, and is fixed at 3.0° in the extratropics. There are 32 vertical levels with 23 levels in the upper 450 m. In the CGCM, a mixed layer model, developed by Noh and Kim (1999) is embedded into the ocean model to improve the climatological vertical structure of the upper ocean.

The ocean model communicates once a day with the atmospheric model. The two component models exchange the following data: SST, wind stress, freshwater flux, longwave and shortwave radiation, and turbulent fluxes of sensible and latent heat. Although any flux correction is not applied, the model does not exhibit a significant climate drift in the long-term simulation. In addition, the current CGCM reasonably simulates the climatology of most oceanic and atmospheric variables. In addition to the climatology, the coupled model realistically simulates ENSO characteristics. Figure 1 shows interannual variability of the tropical Pacific SST in the observation and model. The SST variability of the model is calculated from the long-term simulation of 200 years. The magnitude of SST variability simulated by the coupled GCM is quite similar to that in the observation over the central-eastern Pacific. As with observation, the pattern of the SST is similar, though it is too far extended to the western Pacific unlike the observed one. As well as amplitude and pattern of ENSO, the present coupled GCM has realistic ENSO characteristics on the in terms of the periodicity, seasonal locking, and teleconnection pattern (not shown). Therefore, the present model has a potential to use for the dynamical seasonal prediction.

2.2 Experimental designs

For the T2 seasonal prediction, the experimental seasonal prediction has been carried out with a 4-month lead starting from 1st May during the 23-year period from 1979 to 2001. The initial atmospheric and land conditions are obtained from the NCEP reanalysis data (Kalnay et al. 1996). Six ensemble members are generated using slightly different initial conditions by a lagged approach. The SST boundary condition is identical for all ensemble members.

The T1 seasonal prediction has been carried out using the SNU CGCM. To obtain the initial oceanic conditions, the ocean component of the CGCM is integrated by prescribing the observed wind stress as the surface boundary conditions. Also, the observed SST is nudged with a 5-day restoring time scale. The initial atmospheric and land conditions are obtained from NCEP reanalysis data, which are mostly the same as those in the T2 prediction. Given the initial conditions, the experimental predictions are carried out with a 6-month lead time, starting from 1st May for the period 1979–2001. Six members are used for ensemble prediction.

2.3 Observational data

The SST data used are the observed monthly means from the Improved Extended Reconstructed Sea Surface Temperature Version 2 (ERSST V2) data set (Smith and Reynolds 2004) created by the National Climate Data Center (NCDC). This data analysis uses monthly and 2° spatial superobservations, which are defined as individual observations averaged onto our 2° grid.

The observed precipitation data has been extracted from the Climate Prediction Center Merged Analysis of Precipitation (CMAP) (Xie and Arkin 1997). This dataset utilizes in situ observations, infrared and microwave satellite

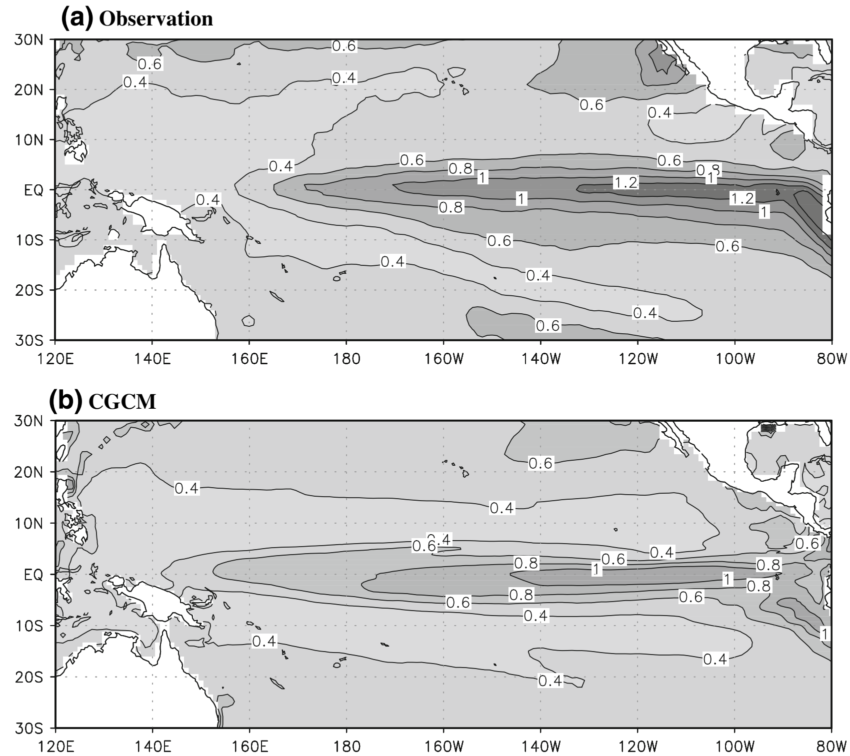

Fig. 1 Standard deviation of monthly SST in **a** the observation and **b** CGCM simulation

observations, and the NCEP/NCAR (National Centers for Environmental Prediction/National Center for Atmospheric Research) reanalysis data to estimate pentad precipitation averaged over an area of $2.5° \times 2.5°$ latitude–longitude. The atmospheric variable datasets such as those for the surface temperature and net surface heat flux are obtained from the NCEP/NCAR reanalysis dataset (Kalnay et al. 1996).

3 Climatological simulation

Prior to evaluating the seasonal predictability, the precipitation climatology is examined in the T2 and T1 predictions. Figure 2 shows the climatology and mean bias of summer mean (JJA) precipitation simulated by the T2 and T1 prediction systems. Generally, the climatology simulations of both the T2 and T1 systems are similar. However, some systematic biases are found in both simulations, as shown in Fig. 2d, e. Interestingly, the bias patterns of the two simulations appear to be similar to each other. For example, there are common dry biases over the Maritime continent and near the Korea–Japan region. On the other hand, the wet biases are found over the Bay of Bengal, Central China, and the SPCZ region. The similarity between the biases of the two simulations indicates that the systematic bias mostly originates from the imperfections in the AGCM.

Although the patterns are similar, the magnitude of the systematic bias tends to be larger in the T2 prediction. The RMS error of the T2 (2.2 mm/day) is larger than that of the T1 (1.9 mm/day) over 40–120°E and 20°S–40°N. The error of the T2 prediction is reduced about 14% in the T1 prediction. The SST climatology simulated by the T1 system has a systematic bias (Fig. 3a). This bias may reduce the benefits of CGCM for predicting atmospheric variability. In contrast to the T1, the T2 does not have any climatological SST bias because it uses the observed SST climatology as explained in Sect. 2. Nevertheless, the T1 has a better climatology of precipitation and other atmospheric variables as compared to the T2 simulation, indicating that the air–sea coupling is critical to correctly simulate the atmospheric climatology.

How does the air–sea coupling play a role to correctly simulate atmospheric climatology? Figure 3 shows the difference in SST and precipitation climatology between the T1 and T2 predictions. The SST difference shown in Fig. 3a is the climatological bias of the T1 prediction because the T2 system uses the observed climatology. Interestingly, it appears that the difference patterns in the SST and precipitation are similar to some extent. For example, the T1 system simulates more (less) precipitation compared to that of the T2 prediction system where warm (cold) SST bias exists. In particular, the coexistence of warmer SST and wetter precipitation is evident in the maritime continent and the northern Indian Ocean. The T2 system has a climatological dry bias in these regions. The similarity between the patterns of SST and precipitation, as shown in Fig. 3, can be understood easily. Generally,

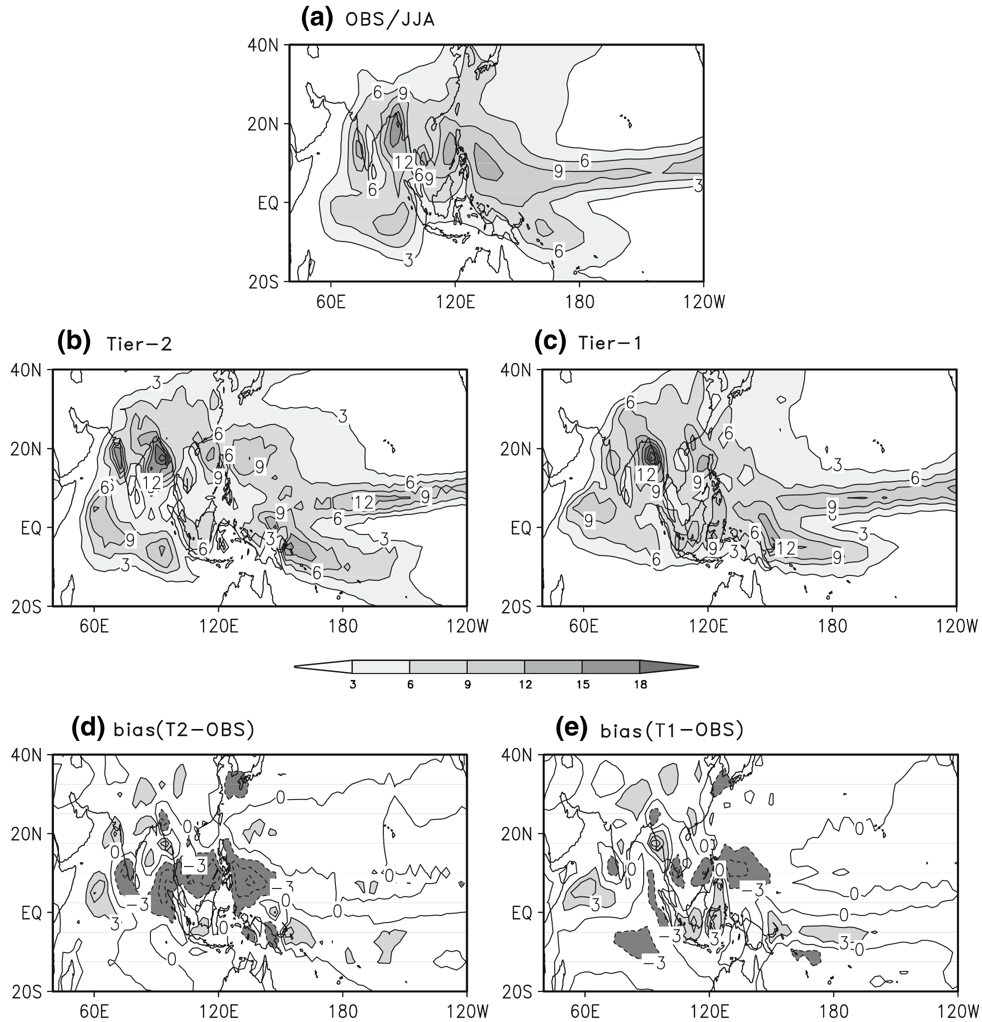

Fig. 2 **a** Climatological summer mean (JJA) precipitation in observation, **b** T2, and **c** T1 predictions and their biases of **d** T2 and **e** T1 predictions

warmer SST produces favorable conditions for greater precipitation by several mechanisms such as the local surface heat flux (Zebiak 1986) and boundary layer flows (Linzen and Nigam 1987).

Figure 4a shows the surface net heat flux difference between the NCEP reanalysis and T2 prediction. Though the NCEP heat flux has an uncertainty, it will be just as useful to compare relative magnitude between the T2 and T1 prediction. Interestingly, the heat flux difference tends to be closely related to the precipitation bias pattern. Therefore, the wet bias can be linked to the negative difference of heat flux by greater cloudiness and solar radiation blocking. The negative heat flux cools the ocean surface and finally induces an additional SST cooling. Similarly, the dry bias can be linked to an additional SST warming. Therefore, the dry (wet) bias of the atmospheric component model can induce SST warming (cooling). However, the T2 system cannot reflect this process because of the lack of feedback to the ocean.

In contrast to the T2 system, the T1 system includes the atmosphere to ocean feedback process. Therefore, the positive heat flux, which is related to the dry bias of the atmospheric component, induces an additional SST warming and can produce a warm SST bias in the T1 prediction. The additional SST warming produces favorable conditions for greater convection and causes increased precipitation over the regions where the atmospheric component intrinsically possesses the dry bias. Similarly, the wet bias of the atmospheric component can also be reduced by the coupled process in the T1 system. Throughout this coupled process of the SST-heat flux-rainfall loop, the difference of surface heat flux from the NCEP reanalysis data in the T1 simulation is noticeably reduced, as shown in Fig. 5b. Therefore, the coupled process in the T1 system reduces the climatological biases of the uncoupled AGCM though the climatological SST bias is introduced.

4 Seasonal predictability

In the previous section, it was shown that the T1 makes a better climatological prediction since it includes the

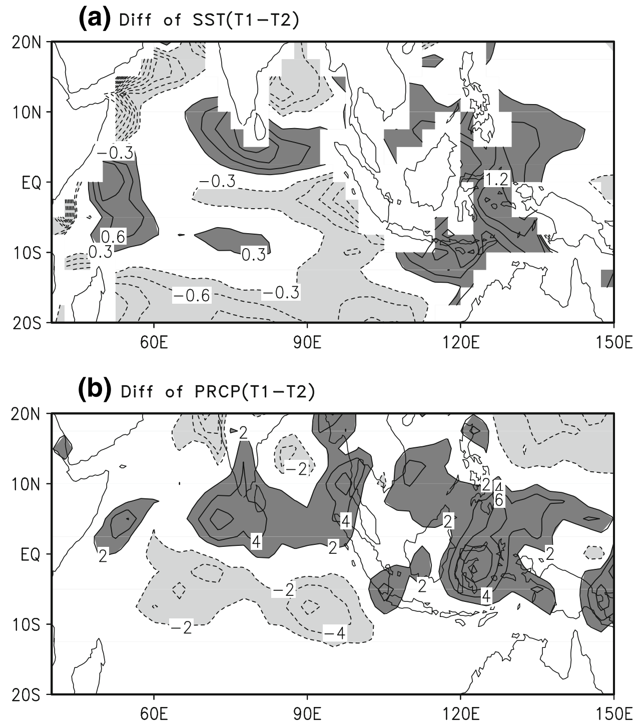

Fig. 3 **a** Climatological SST and **b** precipitation differences between the T1 and T2 predictions. Units are K and mm/day, respectively

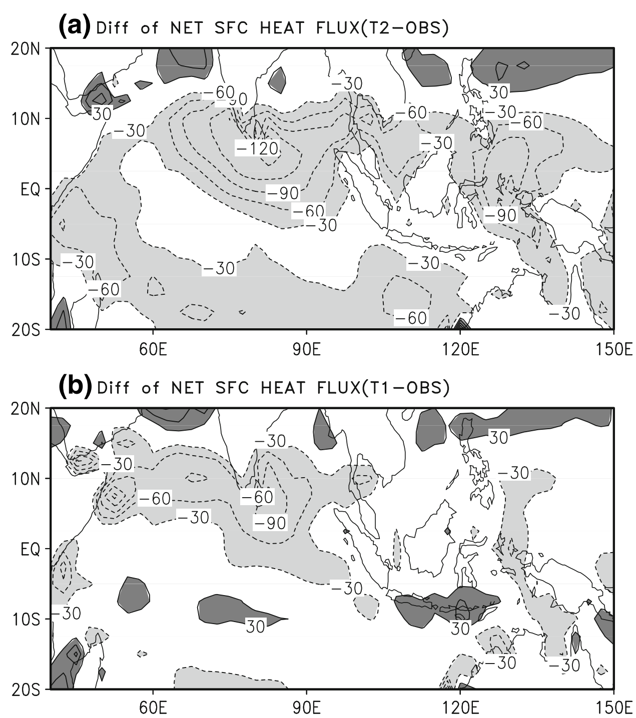

Fig. 4 Climatological bias of net surface heat flux in **a** T2 and **b** T1 predictions. Unit is W m^{-2}

air–sea coupled process. It would be preferable that this improved climatology is related to an improved seasonal prediction. This issue will be further discussed later. In

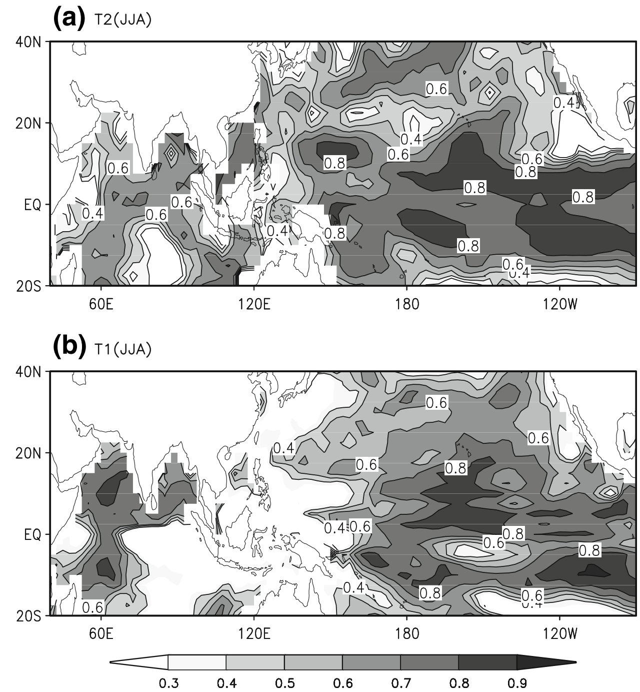

Fig. 5 Coefficients of correlation between the observed SST and the predicted SST of **a** T2 and **b** T1 systems for the period of 22 years

this section, the seasonal prediction skill of the T1 and T2 systems will be evaluated and compared to each other.

Before examining the seasonal prediction skill of the atmospheric variables, the prediction skill of the SST anomaly is compared. It is well known that the SST anomalies are the most crucial factors in determining the seasonal predictability, because they retain a memory of seasonal and interannual time scale. As mentioned earlier, the SST prediction in the T2 system is obtained from the dynamic and statistical ensemble SST prediction system (Kug et al. 2007), which has a predictive skill of up to a 6-month lead time over most tropical oceans. In comparison, the CGCM in the T1 system itself produces SST anomalies.

To examine the predictive skill of the anomalous SST, the correlation coefficients between the observed and predicted seasonal mean (JJA) SSTs were calculated, as shown in Fig. 5. Note that the JJA seasonal mean prediction is 2–4 months lead SST forecast. Both prediction systems have sufficient predictive skills over the ENSO region, although the T2 prediction appears to be slightly better. The correlation skill is more than 0.7 along the equator and more than 0.8 over the off-equatorial region. During the boreal summer, some ENSO events experience a phase transition. At this time, the equatorial SST is nearly zero along the equator; however, a SST signal is observed over the off-equatorial region. Therefore, the correlation skill for the equatorial SST is relatively lower compared to that for the off-equatorial SST.

The T2 SST prediction appears to be better than T1 prediction for areas other than the ENSO region. In particular, the T1 prediction has a substantial bias over the warm pool region. Over the eastern Indian Ocean, the T1 prediction does not have a predictive skill, although the forecast lead time is short. Therefore, it can be concluded that the T2 SST prediction is generally superior to the T1 SST prediction.

The SST predictive skill is a very important factor in the seasonal climate prediction of the atmospheric variables. As discussed in several previous studies, SST anomalies have a significant influence on seasonal mean circulation and rainfall anomalies (Shukla and Wallace 1983; Livezey et al. 1996; Barnett et al. 1997; Kumar and Hoerling 1998). Therefore, it is considered that better SST prediction is related to better prediction of the atmospheric variables. Because the T2 system has a superior SST anomaly prediction as well as SST climatology, its seasonal prediction may be better than that of the T1 system. However, if the T1 has a higher skill for seasonal prediction, it will indicate that the air–sea coupled process is critical to the seasonal predictability.

Here, the seasonal prediction skill for the atmospheric variables is calculated from the predictions for the period of 1980–2001. First, the pattern correlations of the JJA mean precipitation are calculated using the T1 and T2 predictions for three different domains, as shown in Fig. 6. For the global domain, the T1 prediction generally appears to be better than the T2 seasonal prediction. The mean pattern correlation of the T1 and T2 predictions are 0.27 and 0.20, respectively. The correlation difference is significant at a 90% confidence level. Although the T1 is better than the T2 on an average over the 22-years period, there exists a period where the T2 skill is superior to the T1 skill. Prior to 1994, the T1 tends to have a higher correlation than the T2, while the reverse is true for the period from 1995 to 1999. It will be interesting to investigate this type of decadal change in the seasonal predictability. However, this is beyond the scope of the present study.

It is noteworthy that the T1 prediction is relatively superior to the T2 prediction in the warm pool region, where the T1 SST prediction degrades significantly in comparison to the T2 prediction. The T2 system exhibits a poor skill in this region, although the given SST boundary forcing was quite predictive, as shown in Fig. 5. The superiority of the T1 prediction is noticeable over the WNP monsoon region. The T2 skill is occasionally negative. The difference is significant at a 99% confidence level. As summarized in Table 1, the T1 prediction is superior to the T2 prediction with regard to both pattern correlation and RMS error for different regions.

This indicates that the air–sea coupled process is critical to the prediction of precipitation in the warm pool region. Additionally, this result further implies that the variability of precipitation in the warm pool region does not depend simply on the local SST boundary conditions but is also determined by the air–sea coupled process itself in the presence of remote forcings such as ENSO and monsoon heat sources. Therefore, the existence of the air–sea coupled process can be crucial to the seasonal predictability.

To examine how well the T2 and T1 predict precipitation variability, the singular value decomposition (SVD) analysis is applied to the observed and predicted precipitation data. The SVD modes are calculated separately from the T1 and T2 predictions. The SVD vectors and their corresponding time series are displayed in Figs. 7 and 8. Figure 7 shows the first SVD mode, which is related to the ENSO mode. The time series of the first mode is well matched with the observed NINO3.4 SST index (not shown). For both T1 and T2 predictions, the time series are well correlated with the observed time series, and the temporal correlation coefficients of the T2 and T1 predictions are 0.89 and 0.93, respectively. This implies that both predictions satisfactorily capture the dominant ENSO mode. However, the spatial pattern of the prediction is different from that of the observed precipitation in some aspects. In the observations, anomalous positive precipitation appears over equatorial central Pacific, where the strong SST anomaly drives atmospheric motion. The strong precipitation modulates the Walker circulation, thereby inducing sinking motion over the western Pacific region, which is linked to anomalous negative precipitation. In the observations, there are two centers of negative precipitation in the WNP region and the maritime continent region. However, the T2 system does not predict the negative centers correctly. In particular, the sign is actually opposite to that of the observations for regions over the WNP. This indicates that the T2 prediction has a significant systematic bias over this region. The systematic bias may originate due to the absence of the air–sea coupled process. Unlike the T2 prediction, the T1 system has at least the same sign when predicting the negative precipitation over the western North Pacific region, although the magnitude is too weak. Moreover, the overall pattern of the T1 prediction is more similar to the observed pattern. The pattern correlation of the T1 prediction (0.56) with the observed SVD pattern is higher than that of the T2 prediction (0.48).

Figure 8 shows the 2nd SVD mode between the observed and predicted precipitation data. This mode appears to be related to the WNP monsoon. The time series is well correlated to the WNP monsoon index defined by Wang et al. (2001). The SVD time series in the T2 and T1 predictions are well matched. The temporal correlation between the two time series is quite high in both prediction systems. This indicates that the interannual variability of

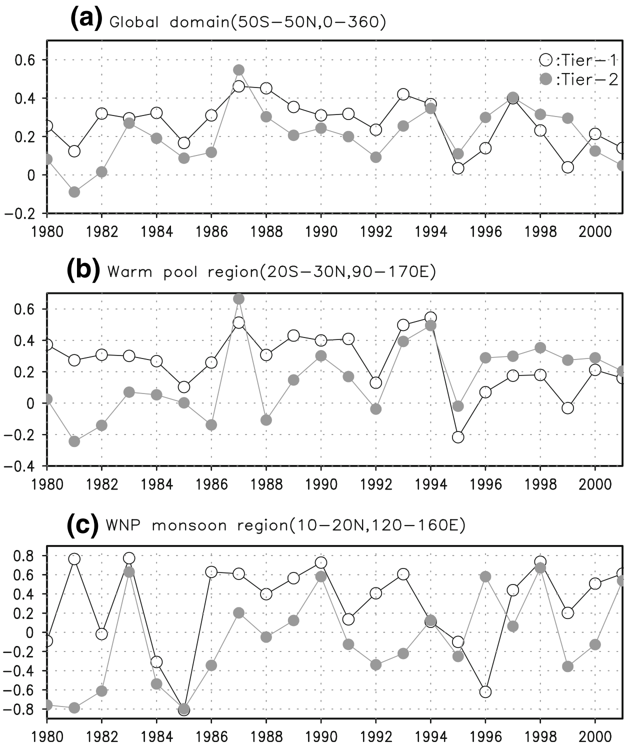

Fig. 6 Anomaly pattern correlation of JJA precipitation of T1 (*open circle*) and T2 (*closed circle*) over **a** global domain, **b** warm pool region, and **c** WNP monsoon region

Table 1 Averaged pattern correlation and RMS error of JJA precipitation

Region	Pattern correlation		RMS error	
	Tier-two	Tier-one	Tier-two	Tier-one
Global	0.20	0.27	1.07	1.00
Monsoon	0.15	0.26	2.00	1.82
WNP	–0.08	0.28	2.54	1.96

the WNP monsoon is predictable in the present T1 and T2 dynamic prediction systems.

In the observational pattern of the SVD mode, the action center of the precipitation is located over the WNP region and two negative centers exist over the maritime continent and the western south Pacific, as shown in Fig. 8a, d. However, to a large extent the SVD pattern of the T2 prediction simulates patterns different from those observed. The positive center over the WNP is shifted slightly eastward, and the negative center over the western south Pacific is somewhat different. Furthermore, the negative center of the maritime continent is completely overlooked. In comparison to T2 pattern, the T1 pattern is quite similar to the observed pattern. The T1 system correctly simulates the single positive center and two negative centers. The pattern correlation of the T1 prediction (0.58) with the observed SVD pattern is significantly higher than that of the T2 prediction (0.31). Most significant biases of the T2 occur over the warm pool region, where its SST prediction is superior to that of the T1 prediction. Therefore, the absence of the air–sea coupled process may induce the systematic biases over this region.

So far, we have demonstrated that the T1 yields a relatively better prediction than the T2, particularly over the warm pool region where the T2 prediction has a more significant bias. This implies that better SST prediction does not guarantee better prediction of the precipitation without the air–sea coupling over the warm pool region. How does the air–sea coupling play a role in simulating and predicting the precipitation variability over the warm pool region? Recently, Wang et al. (2005) indicated that state-of-the-art AGCMs are unable to properly simulate the Asian-Pacific summer monsoon rainfall even when the observed SST is imposed as a surface boundary condition. They further mentioned that all models yield positive SST–rainfall correlations over warm pool region in the seasonal mean time scale that contradicts the observations. The observed lag correlation between the SST and rainfall suggests that the atmosphere leads the ocean over the warm pool region. However, the AGCM cannot simulate the lag correlation because the atmospheric feedback does not exist. The coupled model simulates a realistic SST–rainfall relationship. Therefore, it was concluded that the uncoupled AGCM is inadequate for predicting precipitation variabilities over the summer monsoon and warm pool regions.

Using the present T1 and T2 prediction data, we analyzed and compared the SST–rainfall relationship, which was emphasized by Wang et al. (2005). The T2 prediction does not capture the observed negative correlation between SST and the rainfall over the WNP region, where the prediction has a significant bias. On the other hand, the T1 prediction satisfactorily simulates the SST rainfall because it includes the atmospheric feedback process. Therefore, the T1 prediction has a relatively better precipitation skill owing to the correct coupled process. Although the T2 prediction has an accurate SST prediction, the SST anomaly would induce a precipitation anomaly with the same sign. However, the SST anomaly is actually negatively correlated with the precipitation anomaly because of the atmospheric feedback to the ocean and the oceanic feedback to the atmosphere over the warm pool region. Therefore, the uncoupled T2 prediction has a serious bias over the WNP region.

As discussed above, the SST–rainfall relationship explains why the T2 prediction is problematic. In this study, we will also discuss another aspect of how the air–sea coupled process can reduce the systematic bias of the uncoupled prediction, although it will be eventually linked to the

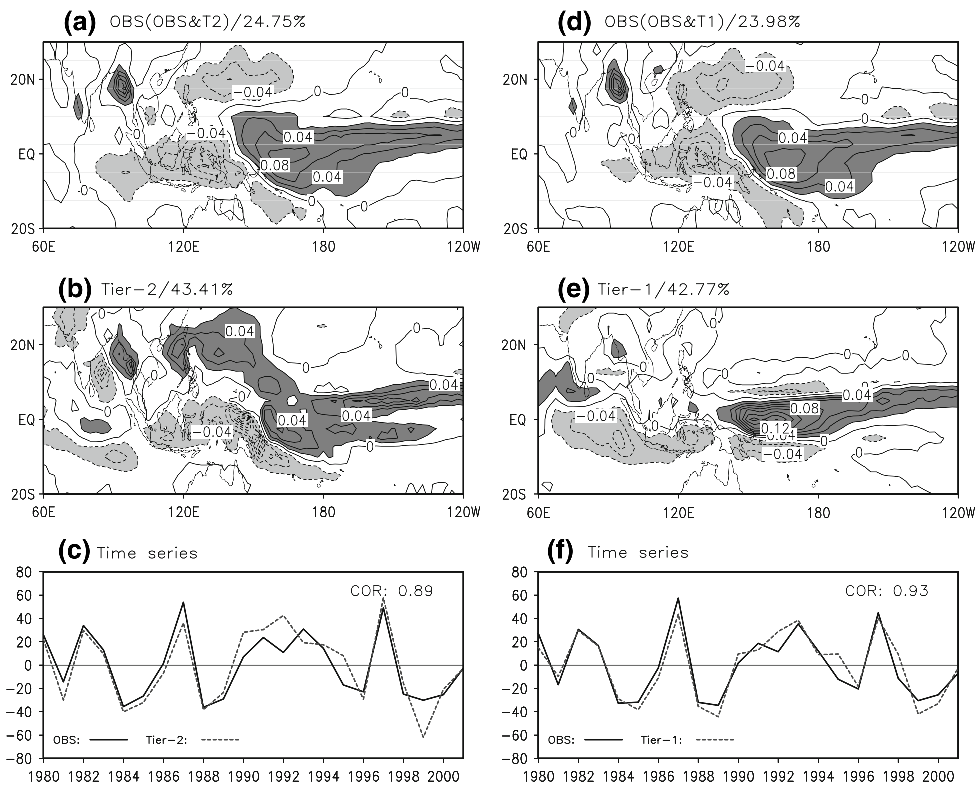

Fig. 7 1st SVD mode for observed and predicted JJA precipitation in T2 (*left panel*) and T1 (*right panel*). The *upper* and *middle panels* show the observed and predicted counterparts of the SVD vectors, respectively. The *lower panel* shows the corresponding time series. The *solid* and *dashed lines* indicate the observed and predicted time series

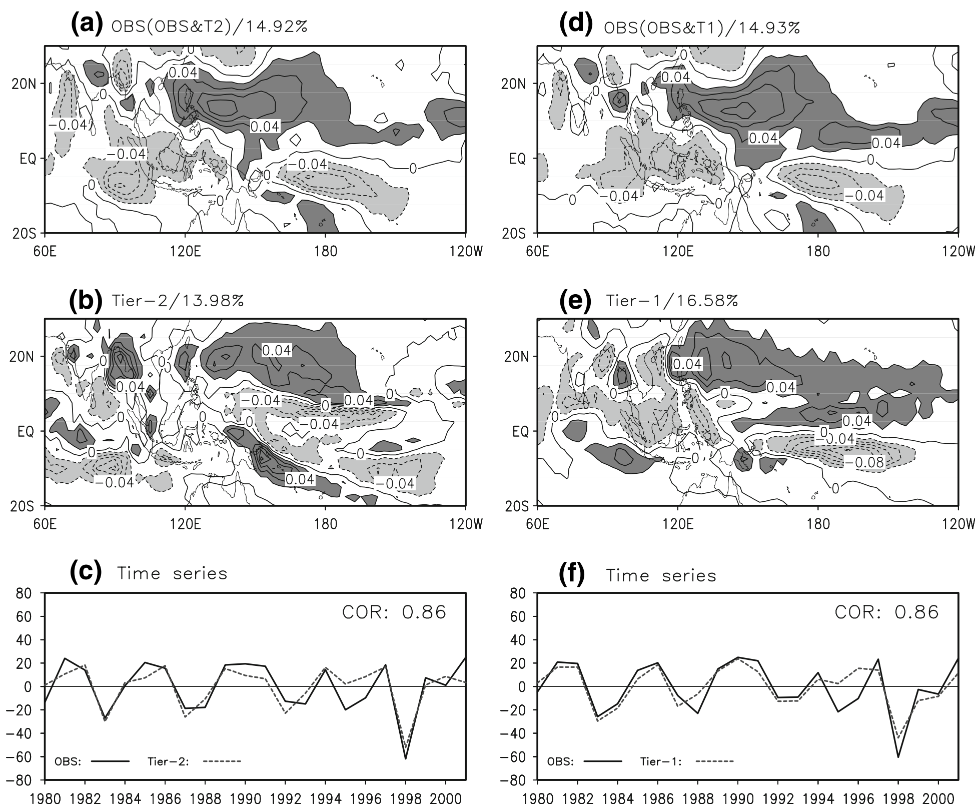

Fig. 8 Same as Fig. 7 except for the 2nd SVD mode

argument by Wang et al. (2005). We will demonstrate how the air–sea coupled process can reduce the magnitude of the systematic bias by suppressing the positive feedback process for anomalous precipitation. This process is similar to the climatological one, which the air–sea coupling can reduce the climatological bias of the uncoupled AGCM.

Figure 9 shows the biases of the precipitation and zonal wind at 850 hPa during the El Nino events. For this composite, the 1982, 1987, 1991, and 1997 El Nino events are used. As expected from Fig. 7, the T2 prediction has a significant bias for the precipitation prediction. In particular, there is a north–south dipole bias of the precipitation over the western Pacific. Corresponding to this bias, there are anticyclonic biases of the zonal wind, as shown in Fig. 9c. The large bias of the T2 prediction may originate from incorrect local SST forcing or remote ENSO forcing. Compared to the T2 prediction, the T1 prediction has a relatively small error in both precipitation and the zonal wind. In the coupled system, if incorrect local SST forcing and ENSO forcing bring about a bias, the coupled process plays a role to reduce the magnitude of the bias. For example, a positive bias of precipitation necessarily accompanies the negative bias of the net surface heat flux by intercepting shortwave radiation due to excessive cloudiness. The correlation between the biases of precipitation and heat flux is quite high (0.86). The negative heat flux leads to additional SST cooling in the coupled system. This additional SST cooling will produce a less favorable condition for the convective system, indicating a reduction in the precipitation. This constitutes negative feedback for the precipitation variability. Further, this indicates that the air–sea coupled process constantly attempts to restore a perturbation to the balanced state. If the perturbation is a model bias of the uncoupled system, the coupled system will adjust the perturbation to the balanced state of the coupled system, which is probabilistically close to the state of the observation. Through this process, the magnitude of the bias can be reduced in the coupled system. In the uncoupled system, however, the heat flux bias cannot affect the SST boundary condition; thus, there is no negative feedback in the SST-heat flux-rainfall loop. This explains why the T2 prediction has a relatively larger bias as compared to the T1 prediction.

Unlike the central-eastern Pacific, ocean dynamics does not play a dominant role in changing the SST in the warm pool region because the thermocline is deep and the horizontal temperature gradient is weak. Therefore, the heat flux can effectively change the SST. Additionally, the small SST change can effectively affect the convective activity because the climatological temperature is high. Owing to these two effects, the negative feedback of the SST-heat flux-rainfall loop is strong, and the T2 system has a significantly large bias over the warm pool region.

It is noteworthy that this negative feedback has to reduce not only the model bias but also model variability because they can be considered as perturbations from the balanced state. Figure 10 shows the variance of the seasonal mean precipitation in the T2 and T1 predictions. The variance is calculated by averaging the variance of each ensemble member. Note that the T1 and T2 predictions use the same initial atmospheric conditions; therefore, the initial condition cannot contribute to the difference in the variance. If the

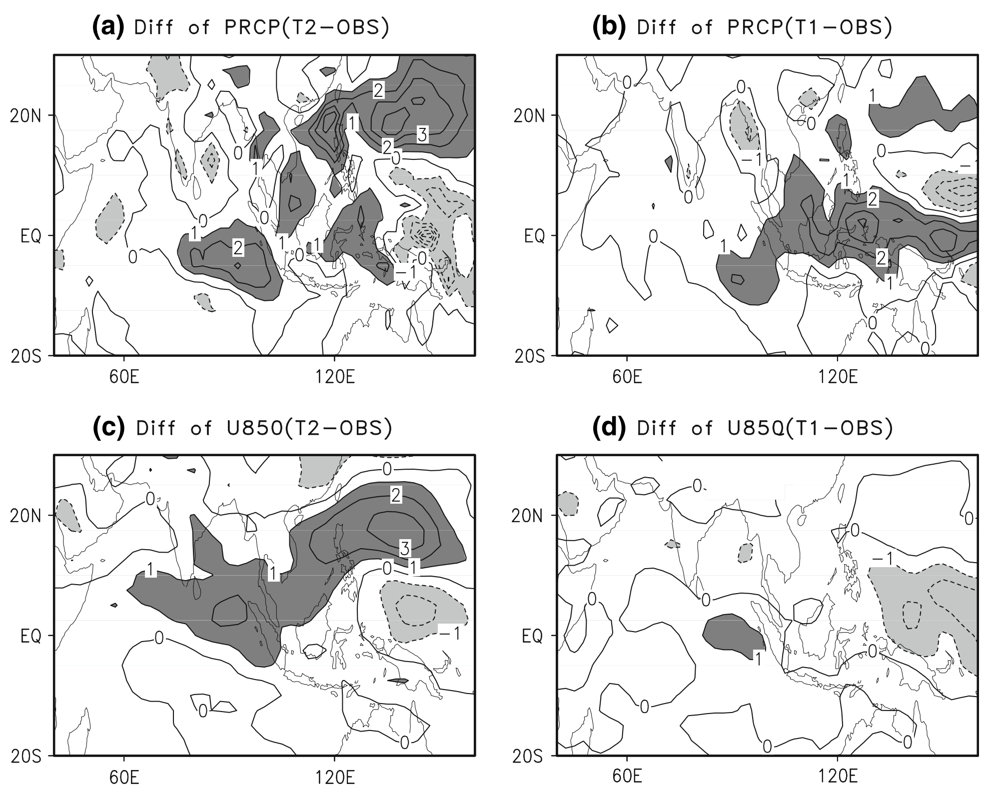

Fig. 9 Errors in precipitation (*upper panel*) and zonal wind at 850 hPa (*lower panel*) for the El Nino composite. *Left* and *right panels* show T2 and T1 predictions, respectively

role of the negative feedback is trivial, we can expect the variance of the T1 to be greater than that of the T2 because each ensemble member of the T1 has a different SST forcing, whereas every T2 ensemble member shares the same SST forcing. However, the T2 prediction has a stronger variance than the T1 prediction over most warm pool regions except the eastern Indian Ocean, where the T1 prediction has an excessive SST variability unlike the observations. A stronger variance of the T2 indicates that the negative feedback plays a crucial role in controlling the precipitation variability over the WNP region. Finally, this result indicates that the negative feedback of the air–sea coupled process can effectively reduce the magnitude of the bias produced by the uncoupled system over the warm pool region.

5 T1 and T2 systems in multi-model seasonal predictions

In the previous section, using the SNU T1 and T2 predictions, we showed that the T2 has a systematic problem in predicting the precipitation variability over the warm pool region due to the absence of the air–sea coupled process. Therefore, the T2 prediction is inferior to the T1 prediction even though T2 has a better SST boundary condition. In order to verify whether these results depend on the models utilized, multi-model T1 and T2 predictions are compared in this section. Although the atmospheric components in the T1 and T2 systems are not identical in the multi-model framework, the comparison will indicate the current status of the T1 and T2 seasonal predictions.

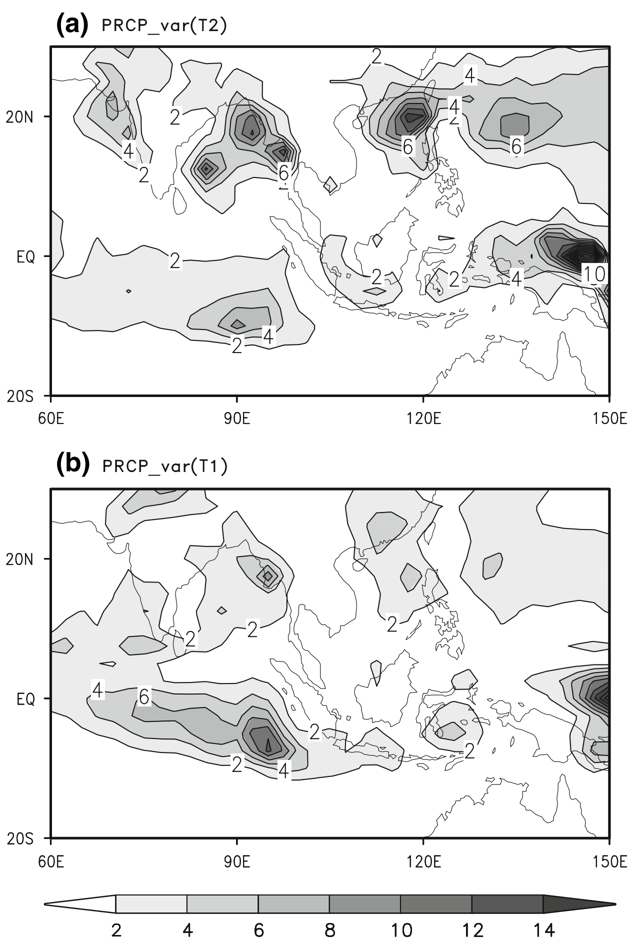

Fig. 10 Variance of JJA mean precipitation in **a** T2 and **b** T1 prediction. The variance is calculated from each ensemble member

For multi-model T1 and T2 predictions, the CliPAS (Climate Prediction and its Application to Society) and DEMETER (Development of a European Multi-Model Ensemble System for Seasonal to Inter-Annual Prediction) models are used. The CliPAS receives seasonal prediction data from five T1 and five T2 systems. For the T2 prediction, all AGCMs were forced by the same predicted SST produced through the Global SST Prediction System, which is the same as that of the SNU T2 prediction. The T1 system consists of NASA, NCEP, SNU, SINTEX-F, and UH, and the T2 system consists of FSU, GFDL, SNU, ECHAM, and CAM2. DEMETER consists of seven CGCMs. The participating groups in the DEMETER project are CERFACS, ECMWF, INGV, LODYC, Meteo-France, Met Office in UK, and MPI (see Palmer et al. 2004). The used hindcast is from 1980 to 2001 for 22 years.

Figure 11 shows the climatological mean biases of the summer mean precipitation of the multi-model ensemble for the CliPAS T1, T2, and DEMETER MME. The CliPAS T2 has a large mean bias over the WNP region and the north Indian Ocean. The mean RMS error of the precipitation is 1.77 mm/day over 40°E–120°W and 20°S–40°N. On the other hand, the CliPAS T1 and the DEMETER prediction systems have relatively small mean biases although each coupled model has a systematic bias of SST climatology. The mean RMS errors of the CliPAS T1 and DEMETER are 1.38, and 1.46 mm/day, respectively. These results are consistent with those of the SNU T1 and T2 predictions, namely, that the air–sea coupled process plays a role in reducing the climatological bias of uncoupled AGCMs.

Next, the seasonal prediction skill of the T1 and T2 predictions is investigated. Figure 12 shows the pattern correlations for the summer mean precipitation over the global domain and warm pool region. The pattern correlation is averaged for the period 1981–2001. Over the global domain, the MME skills of the CliPAS T1 and T2 are 0.38 and 0.31, respectively. The DEMETER model's skill is 0.43 (not shown). Additionally, the skills of the CliPAS T1 and T2, and the DEMETER over the warm pool region are 0.31, 0.23, and 0.36, respectively. The T1 predictions are better than T2 predictions. These results indicate that the state-of-the-art T1 prediction has superior skill as compared to the T2 prediction. When the skills of individual model

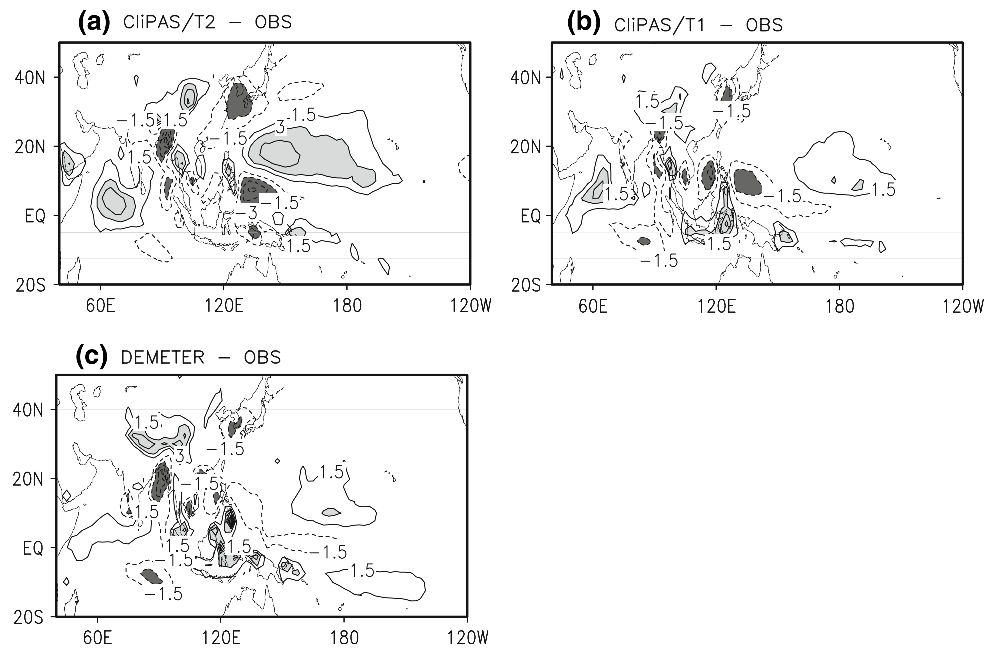

Fig. 11 The climatological mean bias of the summer mean precipitation of **a** CliPAS T2 MME, **b** CliPAS T1 MME, and **c** DEMETER

predictions are compared, most T1 predictions have higher skill than most T2 predictions, although some T2 models have better skill than the worst T1 models. It is noteworthy that the SINTEX-F and ECHAM models share the same atmospheric model; however, their versions are slightly different. The SINTEX-F prediction always has a higher skill than ECHAM prediction in both the global and warm pool regions. This is consistent with the previous SNU results. These results indicate that the air–sea coupled process is a very crucial factor in seasonal predictability.

6 Summary and discussion

In this study, the SNU T1 and T2 seasonal predictions are investigated and compared. The comparison shows that the air–sea coupling is an important factor not only for climatological simulation but also for seasonal predictability. In particular, the air–sea coupling plays an essential role over the warm pool region, where the atmosphere tends to lead the ocean. In this region, the T1 prediction has better climatology and higher seasonal prediction skill despite the presence of a climatological SST bias and poor SST forecast skill. We have suggested here that the air–sea coupled process plays a role to reduce both the climatological and anomalous biases of the uncoupled AGCM by means of the negative feedback of the SST-heat flux-rainfall loop.

The importance of the air–sea coupled process on the seasonal predictability may depend on seasonality. Though we have focused only on the summer mean in this study, we have applied the same analysis for the winter mean prediction. Interestingly, it is difficult to recognize the superiority of the T1 prediction for the winter mean precipitation. These results can be expected because the rainfall–SST relations observed summer and winter are quite different. While the correlation between rainfall and SST is negative during the boreal summer over the WNP region, it is positive during the boreal winter. This implies that the negative feedback of the SST-heat flux-rainfall is relatively weak in the winter basic state. Therefore, the benefit of T1, which include the air–sea coupled process, is relatively reduced and the predictive skill of the atmospheric variables mainly depends on the surface boundary forcing.

Although we argued that the T1 prediction is relatively better than the T2 prediction, both predictions unfortunately still have insufficient skills to supply useful information to the public for most regions except for the ENSO region. However, there is ample scope to improve the T1 prediction system as opposed to the T2 prediction system. Because the predictability of the T2 system originates from the surface boundary condition by the experimental design, the improvement of the T2 prediction has to be achieved by improving the SST prediction. However, it appears to be somewhat difficult to improve the SST prediction distinctively, as the skill of the SST prediction itself is not bad over most tropical regions (Kug et al. 2007). Furthermore, as the main degradation of the T2 skill results from the absence of the air–sea coupled process, the future improvement of the T2 prediction will be limited. On the other hand, the seasonal prediction with the T1 system is now in its initial stage. As shown previously, the SST prediction of T1 is currently very poor; this could be partly attributed to originate from the problem of initialization of

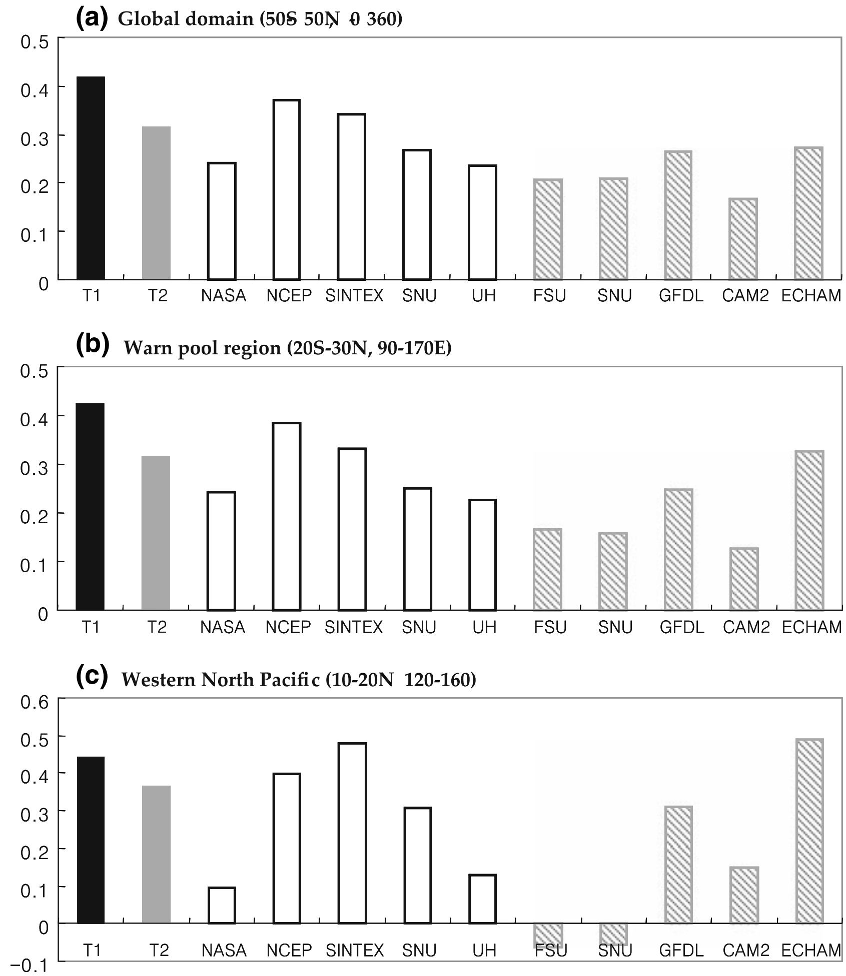

Fig. 12 Time averaged pattern correlation for JJA precipitation over **a** global domain (50°S–50°N, 0°–360°), **b** warm pool region (20°S–30°N, 90–170°E), and **c** western North Pacific region (10–20°N, 120–160°E) using CliPAS T1 and T2 systems. The *filled black* and *gray bars* denote T1 MME and T2 MME, respectively

the current CGCMs. The current CGCMs still have an initial drift problem due to inconsistency between the initial atmospheric and oceanic conditions and imbalance between the initial conditions and model physics. Therefore, it is expected that the skill of T1 can be improved by better initialization in the coupled system.

Many operational centers had adopted the T2 approach for seasonal climate prediction. This T2 system has been used as an alternative technique in the past 10–15 years because the performance of the CGCMs was very poor during that period. Apart from the lack of computing resources, the initial drift of the CGCMs was the main problem in using the T1 system. However, since the CGCM has significantly improved and computing power has rapidly increased, the T1 systems have become potential candidates for seasonal climate prediction in recent years. Currently, some operational centers (e.g., NCEP and ECMWF) have changed their seasonal prediction system from T2 to T1, but the others continue to use the T2 system. Therefore, this is a period of transition from the T1 to T2 systems. In this study, we compared the current status of the state-of-the-art T1 and T2 seasonal predictions. We expect that the results of this study can provide a guideline for operational centers that are making seasonal prediction.

In this study, we have continuously addressed the role of the air–sea coupling and its importance on seasonal predictability by means of the SNU T1 and T2 prediction data. However, the prediction data give good information for operational superiority of the T1 system but have a limitation to exactly examine the role of air–sea coupling on simulating climate variability because there are two inconsistencies between the experimental design of the T1 and T2 prediction systems. First, the resolution of atmospheric component is different between the T1 (T42) and T2 (T63) system. Second, the anomalous SST prediction is not same between two predictions. Although the T2 prediction tends to have better atmospheric resolution and better anomalous SST prediction that those of the T1, the differences may disturb to precisely examine the role of the air–sea coupling on the seasonal predictability. To avoid this problem, the anomalous SST predicted by the T1 will be prescribed as a surface boundary condition of the T2 prediction with exactly same atmospheric GCM. Authors would like to leave this experiment in next study.

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