Atmosphere-Driven Cold SST Biases Over The Western North Pacific in The GloSea5 Seasonal Forecast System

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Atmosphere-driven cold SST biases over the western North Pacific in the GloSea5 seasonal forecast system

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Abstract The predictability of the sea surface temperature (SST) in seasonal forecast systems is crucial for accurate seasonal predictions. In this study, we evaluate the prediction of SST in the Global Seasonal forecast system version 5 (GloSea5) hindcast with particular interest over the western North Pacific (WNP) in which the SST can modify atmospheric convection and the East Asian weather. GloSea5 has a cold SST bias in the WNP that grows over at least 7 months. The bias originates from the surface heat flux in which the

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latent heat flux bias shows the biggest contribution. We identify the overestimated cloud in the first few days after initialization that causes insufficient shortwave radiation and negative bias of the surface net heat flux. Uncoupled ocean model experiments infer that the ocean model is unlikely the primary source of the SST bias.

Keywords GloSea5 · SST bias · Seasonal prediction

1 Introduction

Seasonal forecast systems (SFSs) aim to provide an overview of the atmospheric and oceanic conditions a few months in advance (Shukla et al, 2000; Troccoli, 2010). SFSs have evolved to become more complex over the last couple of decades by including varying components to better represent the climate system (Wang et al, 2009). Consequently, SFSs have displayed improved performance in the prediction of important variables such as temperature and precipitation for the next season and potentially allow us to reduce socioeconomic damage from extreme weather events. As the demand for accurate seasonal forecasting has increased, several institutions worldwide have been developing and operating SFSs (e.g. Troccoli, 2010).

SFSs focus on predictions on a timescale of months, in which the interactions of the components of the Earth system cannot be neglected (Neumann et al, 2019), and sea surface temperature (SST) plays a key role in the interactions between the atmosphere and ocean. The changes in SST alter the upper ocean stratification, vertical mixing, and eventually the exchange of heat, momentum and tracers between the surface and subsurface ocean. SST modulates the surface heat fluxes that affect the atmospheric boundary layer and subsequently change the atmospheric circulation and precipitation both

locally and remotely (Bayr et al, 2019; Garfinkel et al, 2020; Ashfaq et al, 2011; Jong et al, 2018; Keeley et al, 2012).

The SST biases in SFSs are common as they can be accumulated as the integration proceeds when the air-sea interactions are not well represented. For example, some coupled general circulation models (CGCMs) suffer from warm SST biases in the tropical southeastern Atlantic and cold biases in the equatorial cold tongue (Li and Xie, 2012; Wang et al, 2014; Toniazzo and Woolnough, 2014; Richter, 2015; Zuidema et al, 2016; Voldoire et al, 2019). Warm SST biases in the tropical Atlantic Ocean are attributed to the errors in the surface heat flux (Toniazzo and Woolnough, 2014), whereas incorrect zonal wind can cause cold SST biases in the Pacific cold tongue by inducing strong upwelling (Vannière et al, 2013). Another example is the cold bias in climate models over the North Pacific that is attributed to either incorrect local surface heat fluxes or the remote influence from North Atlantic biases (Zhang and Zhao, 2015; Wang et al, 2018).

The western North Pacific (WNP; 120–160°E and 0–30°N in the present study) is a key region displaying local and remote influences on atmospheric circulation. It hosts the western Pacific Warm Pool with the highest SST in the globe (Yan et al, 1992), and it is the place where deep convection develops and distributes energy to remote regions (Park and An, 2014; Park et al, 2017). Major ocean currents, such as the Kuroshio Current and Indonesian Through-flow transport large amounts of heat out of this region (Dunxin and Maochang, 1991; Jo et al, 2014). Furthermore, the atmospheric or oceanic variabilities in the WNP can affect other tropical regions via Walker circulation and extra-tropical regions via Hadley circulation (Park and An, 2014). For example, the ocean-atmosphere interactions in the WNP play a key role in Pacific-East Asian teleconnection (Wang et al, 2000). Additionally, SST variability in the western Pacific Warm Pool influences the East Asian summer monsoon and

related rainfall (Huang et al, 2003), in addition to the geopotential height in the North Pacific and North America via atmospheric teleconnections (Park et al, 2017). Hence, the performance of SFSs in forecasting SSTs in the WNP must be carefully evaluated to improve the seasonal prediction for local and remote regions.

In the present study, we evaluate the ability of the Korea Meteorological Administration (KMA) Global Seasonal forecast system version 5 (GloSea5; MacLachlan et al, 2015) to predict the SST in the WNP in the seasonal time scale. GloSea5 provides seasonal forecasts in several institutions, including the UK Meteorological Office and KMA. This operational system produced the hindcast from 1991 to 2016 by integrating the coupled system for seven months starting from reanalysis or data-assimilated states. The SST in the GloSea5 hindcast is anticipated to be consistent with the observations within the time scale when the ocean states still remember the initial condition. However, the extent and growth rates of SST biases beyond this time scale remain unclear, especially in the WNP. For this reason, the SST biases in the WNP in the GloSea5 hindcast are first evaluated. Then, we utilize the surface heat flux dataset to explore how air-sea interactions create and develop SST biases in the WNP. We use the ocean-only simulations to identify the main cause of SST bias development.

This paper is structured as follows. After the description of the data and method in section 2, the SST biases in GloSea5 hindcast are identified in section 3. The causes of the SST biases are explored in section 4, followed by a description of the processes of rapid error development in section 5. The paper ends with a discussion and conclusions in section 6.

2 Data and Methods

We examine the SST predictability using the 1991–2016 KMA hindcast data of GloSea5 (MacLachlan et al, 2015; Williams et al, 2015). GloSea5 is based on coupled Met Office Hadley Centre Global Environment Model version 3 (HadGEM3; Hewitt et al, 2011). The GloSea5 consists of the following components: Met Office Unified Model version 8.6 (UM; Walters et al, 2017), Joint UK Land Environment Simulator version 4.7 (JULES; Walters et al, 2017), Nucleus for European Modeling of the Ocean version 3.4 (NEMO; Megann et al, 2014), and the Los Alamos Sea Ice Model version 4.1 (CICE; Rae et al, 2015). The GloSea5 hindcast is a mean of three ensemble members that are initialized on the 1st, 9th, 17th, and 25th of each month and then integrated for seven months. The initial conditions of the atmosphere and land surface are from the European Centre for Medium-Range Weather Forecasts ERA-Interim project (ERA-Interim, Dee et al, 2011). Those for the ocean and sea-ice are created by NEMOVAR (Mogensen et al, 2009).

We evaluate the SST in GloSea5 against the UK Met Office Hadley Centre’s sea ice and SST dataset (HadISST), the monthly mean SST with a spatial resolution of 1° (Rayner et al, 2003). The surface fluxes in the GloSea5 are also evaluated as they are potential sources of SST biases. The surface fluxes and momentum flux in GloSea5 are compared with those in the ERA-Interim reanalysis dataset, as it provides the initial condition for atmospheric fields of the GloSea5 hindcast.

To assist the source identification of the SST bias in GloSea5, we compare the GloSea5 hindcast with the simulations using the ocean model component of GloSea5, with the same horizontal/vertical resolution. We launched 12 cases each having a total period of 7 months using the atmospheric condition from the DFS5 data (Dussin et al, 2016) that is based on ERA-interim. These sim-

ulations do not have active air-sea interaction but are forced by consistent global forcing that suppresses the possible introduction of error from the surface fluxes.

We analyze the SST biases by the lead time defined as the time difference between the prediction and initialization. For example, the SST bias with a lead time of one month represents the mean SST differences between the first month of each hindcast integration and the HadISST data corresponding to that month. As no data is available for several months of 1991 in cases when the lead time was larger than one month, the analysis is conducted from 1992 to 2015 (288 months). The surface heat and momentum fluxes in GloSea5 are compared with ERA-interim data in the same manner.

3 Prediction Skill of SST

First, we evaluate the SST difference between GloSea5 and HadISST at a lead time of one month, immediately after model initialization. Apart from the near coastal regions, the magnitude of the SST differences between GloSea5 and HadISST averaged over 228 months is less than 0.5 °C (Fig. 1(a)). This is expected as the SST is updated using observations from data assimilation when starting the model. As the integration continued, the SST biases in the North Pacific grow and become organized. The SST with a lead time of six months, which is used for the seasonal prediction, has an overall cold bias in the WNP and a warm bias in the northeast Pacific, and the magnitude of the bias exceeds 1.0 °C in some areas (Fig. 1(b)). A pattern with strong cold biases appear in the equatorial cold tongue, which has also been observed in other CGCMs (Vannière et al, 2013).

The SST biases in the WNP (black box in Fig. 2(a)) are initially negative in some areas that become more negative over the seven months of integration

Fig. 1 Annual mean sea surface temperature(SST) bias of GloSea5 hindcast from 1992 to 2015 with respect to HadISST at a lead time of (a) 1 month and (b) 6 months. Gray lines indicate zero bias, and black solid and dashed lines indicate contours of the biases with an interval of 0.5°C .

(Fig. 2(a)–(g)). The largest negative SST bias is found near the latitude of 20°N where it became larger than -1°C (Fig. 2(g)). The box plots of the SST bias over the WNP show an interquartile range that is in the negative after a lead time of two months, suggesting that cold biases occur in 75% or more of the entire 288-month period (Fig. 3(a)). The growth of negative SST bias shows that almost all months have colder SSTs than observation at a lead time of seven months.

This cold bias is similar to that in climate models. The ensemble mean of historical runs of CMIP5 models has lower SSTs in the North Pacific than the

Fig. 2 (a)–(g) Annual mean SST biases (shaded, °C) from 1992 to 2015 at a lead time (LT) of 1–7 months in the western North Pacific(WNP). (h) The annual-mean SST biases of UKESM from 1992 to 2014. The black box in (a) denotes a WNP area.

Fig. 3 (a) Box plots for the annual mean SST biases ($^{\circ}\text{C}$) averaged in a WNP area (black box in Fig. 2(a)) with a lead time of 1–7 months. (b) Monthly mean SST biases ($^{\circ}\text{C}$) averaged in a WNP area in a lead time of 1 (red) to 6 (blue) months. (c)((d)) Box plots for WNP SST biases of the June (December)-start model ($^{\circ}\text{C}$) with a lead time of 1–7 months. Box plots denote median biases (orange lines) and interquartile ranges (IQR; boxes). The whiskers denote the range of biases, except outliers. Open circles denote the outliers.

observations (Wang et al, 2014; Richter, 2015; Wang et al, 2018). UKESM, an Earth system model based on HadGEM3, also shows a similar long-term SST bias (Fig. 2(h)); there is a negative SST bias larger than -1°C in the western Pacific similar to that in GloSea5. Since UKESM and GloSea5 share the same model frame, one can argue that the SST bias in the UKESM's historical run is developed rather quickly in several months based on the SST bias growth in GloSea5. Furthermore, the processes responsible for the SST biases in GloSea5 can be applied to UKESM.

The development of SST bias differs depending on the starting month. Monthly averaged SST with a lead time of one month follows the observation

Fig. 4 Annual mean surface net heat flux bias from 1991 to 2015 with respect to ERA-interim with a lead time of (a) 1 and (b) 2 months. Black lines indicate contours of biases with an interval of 10 W/m². (c) Time series of biases of the surface heat flux (W/m²) averaged from 1991 to 2015 for 255 days after starting the model. Black, red, yellow, green, and blue lines denote the total surface heat flux (Q_{net}), shortwave radiative flux (SW), longwave radiative flux (LW), sensible heat flux (SH), and latent heat flux (LH), respectively. Positive and negative signs indicate fluxes into and out of the ocean, respectively.

166 closely, but with a six-month lead time it is colder than observations (Fig.
 167 3(b)). The negative SST bias in the 6th integration month is greater during
 168 the boreal autumn and winter; i.e., the bias size is higher than 0.6 °C from
 169 September to December but lower than 0.5 °C from February to June. This is
 170 associated with the rapid development of overall negative biases when starting
 171 in June, which is in contrast to the relatively slow bias development when
 172 starting in December (Fig. 3(c) and (d)).

173 4 Possible Causes of Errors

174 We attempt to find the cause of the annual cold SST biases in the WNP from
 175 the surface heat flux biases in the GloSea5 hindcast. The comparison of the
 176 surface net heat flux with ERA-interim shows both weak negative and positive

values in the WNP in a lead time of one month. Then the bias becomes overall negative in the second month (Fig. 4(a), (b)). The daily total net surface heat fluxes (Q_{net}) are partitioned into shortwave radiation (SW), longwave radiation (LW), sensible heat (SH), and latent heat (LH) fluxes, and each of them is examined against ERA-interim data (Fig. 4(c)). The bias of Q_{net} spatially averaged over the WNP is negative in most of the hindcast period, indicating that the ocean in GloSea5 receives less heat from the atmosphere than suggested by ERA-interim. It is clear that the excessive heat loss by LH is the primary reason for the negative Q_{net} bias. The biases of the LW and SH are relatively small hence not the main source of the negative SST bias. Although the size of the Q_{net} bias gradually decreases, it is still negative, making the cold SST bias grow over time in the WNP.

The excessive heat loss through LH accounts for most of the Q_{net} bias as shown above. LH is calculated by the following equation:

$$LH = \rho_{air} L_e C_L u_{10} (q_{air} - q_*(SST)) \quad (1)$$

where ρ_{air} is the air density at the surface, L_e is the latent heat of evaporation, C_L is a stability-dependent bulk transfer coefficient for water vapor, u_{10} is the wind speed at a height of 10 m, and $(q_{air} - q_*(SST))$ is the difference of the specific humidity in the atmosphere and at saturation for a given SST. Eq. (1) suggests that a negative LH bias can be caused by overestimated 10 m wind speed (u_{10}), underestimated specific humidity of the atmosphere (q_{air}) and/or overestimated SST.

In the WNP, the misrepresentation of the q_{air} generally has a greater impact than that of the u_{10} on the negative LH bias (Fig. 5). During the first 2 months when the size of the LH bias is the biggest (Fig. 4(c)), the LH and specific humidity biases are both negative in the WNP. During this period,

Fig. 5 (a)-(c) The annual mean bias of the LH (W/m^2), lower atmospheric specific humidity (q_{air} ; g/kg), and 10-m wind vector at a lead time of 1 month. (d)-(f) Same as (a)-(c), with a lead time of 2 months. The biases are calculated with respect to ERA-interim. Dotted regions indicate significance of correlation coefficients between LH bias and q_{air} bias at the 95% confidence level. The wind vectors are the differences of between GloSea5 and ERA-interim data.

there is a weak westerly wind anomaly that weakens the easterly wind in the annual mean wind in this area. The SST could not be the candidate of the negative LH bias as the SST is colder than the observations. Therefore, the dry atmosphere in GloSea5 is vital for the negative bias of LH.

In some cases, however, too fast wind speed causes the negative LH bias. For example, the hindcast started in June exhibits a rapid change of SST bias

➤ 6월 시작 모델
Latent heat flux bias (GloSea5 - OAFlux)

Fig. 6 Same as Figure 5, except that the data is from the start of June(0601).
Figure 6.

from positive to negative in the first two months (Fig. 3(c)), which is associated
Wind bias (GloSea5 - ERA interim (내기받은 월자료))
with a LH bias change (Fig. 6(a), (b)). In the WNP region (black box in Fig.

6(a)), the negative LH bias develops in the second month (Fig. 6(d)). The negative
 q_{air} bias becomes positive in the eastern side (Fig. 6(e)). The magnitude of the
10-m wind anomaly grew in the second month (Fig. 6(f)), which can enhance
the seasonal southwesterly. It suggests that the strong southwesterly wind
anomaly forces the evaporative cooling at a lead time two months more than
what a drier atmosphere does.

Fig. 7 (a) July-mean SST bias (shading; °C) and 10-m wind bias (stream line) of the GloSea5 from the start of June (0601) at a lead time of 2 months. (b) July-mean total precipitation rate bias ($\text{kg m}^{-2} \text{s}^{-1}$) of the same data. The bias of the SST is calculated with respect to HadISST. The biases of 10-m wind and total precipitation rate were calculated with respect to the ERA-interim.

According to Wang et al (2000) and Tao et al (2017), the strong southwest-
 erly wind anomaly in the WNP could be associated with a remote response
 to a cold SST anomaly in the equatorial East Pacific (EP). When the EP
 becomes colder, similar to that in the La Niña condition, precipitation in the
 Central Pacific (CP) is suppressed, which drives an anticyclonic circulation
 in the CP and a cyclonic circulation in the WNP. These circulation changes
 eventually develop a southwesterly wind anomaly in the equatorial western
 Pacific. These processes seem to explain the bias patterns in GloSea5, par-
 ticularly in the hindcast started in June (Fig. 7). In the second month, the

Fig. 8 SST bias ($^{\circ}\text{C}$) growth with respect to the lead time for (a) GloSea5 during the entire period, (b) GloSea5 during 2003, and (c) NEMO during 2003.

GloSea5 hindcast shows cold SST biases in the EP region and 10-m wind biases of cyclonic circulation in the WNP (Fig. 7(a)), which is consistent with the observed patterns. The negative bias of the total precipitation rate in the CP and a positive bias related to the cyclonic circulation anomaly in the WNP also are in line with the anomaly patterns suggested in the previous studies (Fig. 7(b)).

To confirm that the surface forcing is the main source of the SST bias in the WNP in GloSea5, we evaluate the SST of the uncoupled ocean model, NEMO, integrated from the same initial conditions as for GloSea5. We ran 12 cases that started on the 1st day of each month in 2003; this year showed a similar bias growth to the averaged one over the entire period (Fig. 8). Horizontal distribution of the monthly mean SST bias with a lead time of one month

► SST bias (2003 – 2004) for Lead time = 1, 6 month

Fig. 9 Horizontal distributions of SST biases (shaded, °C) for (a) and (b): GloSea 5 and (c) and (d): NEMO (ocean model), which is initialized for each month of 2003. (a) and (c) are the biases with a lead time of 1 month; (b) and (d) are the biases with a lead time of 6 months.

is similar in both the hindcast and the ocean model (Fig. 9(a), (c)). After six months of integration, the negative SST bias appears near the equatorial Pacific in NEMO similar to that in GloSea5, although the negative bias areas are limited to the eastern part (Fig. 9(b), (d)). In the WNP, however, NEMO shows a weak positive SST bias ($< 0.5^{\circ}\text{C}$) that can be contrasted to the negative SST biases in GloSea5. These results suggest that the ocean dynamics and thermodynamics in the ocean model do not simulate the SST colder than the observation when the surface forcing is provided by the atmospheric reanalysis data. Thus, the bias in the surface heat flux is the primary source of the cold SST bias in the WNP in GloSea5.

5 Rapid Development of the Surface Heat Flux Bias

In section 4, we confirmed that the negative Q_{net} bias with the biggest contribution from the LH bias is the main source of the SST bias in the WNP. In addition, within the first few days when the Q_{net} bias changes from positive

Fig. 10 Annual-mean surface heat flux biases (W/m^2) from 1991 to 2015 with respect to ERA-interim at a lead time of (a)–(c) 1 day and (d)–(f) 31 days. (a) and (d): Q_{net} biases, (b) and (e): SW biases, and (c) and (f): LH biases. Contour lines mark 10 W/m^2 intervals.

to negative, the SW bias also significantly contributes to its development (red curve in Fig 4 (c)). The positive Q_{net} bias is largely explained by the positive SW bias in the first day of integration (Fig. 10(a)–(c)). On the 31st day, the Q_{net} bias becomes negative in most regions, especially in the Philippine Sea, showing a large negative bias over -30 W/m^2 . In the area indicated by the black square (Fig. 10(a)), the average change of the Q_{net} bias is -39 W/m^2 over 30 days of lead time, and those of the SW and LH are -23 and -18 W/m^2 , respectively, during the same period. Hence, the rapid change in the SW bias

considerably contributes to the development of the negative Q_{net} bias during the first month of the model.

The rapid reduction in SW is associated with clouds in the model. Clouds with a high albedo reflect solar radiation and reduce the SW entering the sea surface. The cloud development is estimated using the cloud radiative effect (CRE) denoted by the difference in the upward radiation between all-sky (with clouds) and clear-sky (without clouds) conditions at the top of the atmosphere (TOA).

$$CRE_{SW} = SW_{all-sky}(TOA) - SW_{clear-sky}(TOA). \quad (2)$$

As positive $SW(TOA)$ represents an upward flux, clouds with high albedo make the CRE_{SW} more positive. The outgoing longwave radiation is affected by the existence of clouds, which can be quantified by CRE_{LW} .

$$CRE_{LW} = LW_{all-sky}(TOA) - LW_{clear-sky}(TOA). \quad (3)$$

Clouds can result in negative CRE_{LW} as they suppresses the outgoing longwave radiation.

In GloSea5, both CRE_{SW} and CRE_{LW} increase in size during the first 31 days (Fig. 11). The difference in CRE_{SW} between the 31st and 1st days (ΔCRE_{SW}) is positive in the WNP, indicating that the amount of clouds increases during the first month of simulation. The addition of clouds is concentrated near the equator where active convection is anticipated as seen in the maximum positive CRE_{SW} (Fig. 11(a)). This region coincides with that in which the SW negative bias developed in Fig. 10(e). The ΔCRE_{LW} also suggests the accumulation of clouds in the WNP within a month after initialization (Fig. 11(b)). A closer investigation reveals that CRE_{SW} and CRE_{LW} develop quickly within a few days (Fig. 11(c)), suggesting that GloSea5 hindcast underwent an adjustment after initialization. GloSea5 hindcast considers

Fig. 11 (a)((b)) Change in the cloud radiative effect (CRE; W/m^2) on SW (LW) from lead times of 1–31 days. Contour lines mark 10 W/m^2 intervals. (c) CRE growth (W/m^2) with respect to the lead time for SW and LW in the WNP region (black boxes in (a) and (b)).

the initial conditions from independent sources; the atmospheric initial condition is from ERA-Interim whereas NEMOVAR updates the initial conditions of oceanic and sea-ice. We anticipate that the erroneous air-sea fluxes can occur and induce errors in both the atmospheric and oceanic components when the atmosphere-ocean coupled states approach the balanced state. Hence, starting the hindcast from the balanced atmospheric and oceanic states could reduce the rapid growth of the Q_{net} and eventually SST biases.

6 Discussion and Conclusion

GloSea5 is a seasonal forecast system used in many institutes, and the diagnostics of the SST bias and possible errors in the system are critical as they can influence air-sea interactions and seasonal prediction. We find a negative SST

bias in the WNP in the GloSea5 hindcast when compared with satellite-based
 observations. The initial SST bias is not significant as the initial condition
 of the ocean is the product of data assimilation. However, cold bias devel-
 oped over the seven months of integration, after which the SST bias becomes
 comparable to that in the multiyear simulation of the climate model. This is
 mainly because of the smaller net heat uptake of the ocean with the biggest
 contribution from excessive LH loss. Within a couple of days, the negative net
 heat uptake bias is accelerated by the decreased positive SW bias stemming
 from the accumulation of clouds reflecting the incoming solar radiation. Al-
 though the average total heat flux bias tapers slowly after 31 days, it is still
 negative; thus, the SST cold bias continues to develop.

The annual negative LH bias is caused by the lower atmospheric specific
 humidity of GloSea5. However, there are times when the source of the LH bias
 is strong wind speed. In summer, climatological southerly winds blow in the
 WNP. For the hindcast started in June, there is a strong southwesterly wind
 anomaly at a lead time of 2 months, which could enhance the southerly of
 GloSea5. Strong wind results in excessive LH to be released at the sea surface.

The rapid error growth in the SW suggests that the initial shock could
 severely degrade the hindcast. The imbalance in the atmospheric and oceanic
 states could create unwanted processes in either the atmosphere or ocean and
 cause erroneous fluxes between them (Rosati et al, 1997; Zhang et al, 2020).
 In the GloSea5 hindcast, the amount of clouds quickly increases in a couple of
 days after initialization, thereby reducing the incoming solar radiation to the
 ocean. The accumulation of clouds reduces the outgoing longwave radiation;
 however, it has a smaller impact than the incoming SW radiation. This error
 may be resolved if the couple data assimilation was applied to the GloSea5
 hindcast data (Sugiura et al, 2008; Mulholland et al, 2015).

The analysis of SST bias in WNP highlights the interactions between the atmosphere and ocean. The initial cloud accumulation rapidly accompanies the increase of the LH loss (Fig. 4(c)), suggesting that the ocean provides moisture for the cloud formation in the first month. The reduced SW radiation and excessive LH loss can lower the SST, which in turn decreases the LH loss and cloud content by reducing the saturation water vapor pressure and evaporation, respectively. This negative feedback appears to work after 60 days when the magnitudes of LH loss bias and SW radiation biases started decreasing. However, the reduction in errors do not occur as fast as their accumulation.

The uncoupled ocean model experiments, which do not show the cold SST biases in the WNP, support that the surface forcing plays an important role in the occurrence of the SST bias. However, one cannot completely rule out the ocean dynamics and thermodynamics as the source of the SST bias. Since the biases of the surface forcing can alter ocean circulation, the GloSea5 hindcast and the ocean model do not have the identical circulation. Hence it is possible that the biases of the surface fluxes were passed to the ocean, which eventually contributes to the development of the SST.

The WNP overlaps the Pacific Warm Pool where strong convection occurs. Through Walker and Hadley circulation the conditions of the WNP can affect a wide area. The East Asian monsoon, which is vital for inducing precipitation in densely populated East Asia, is also closely related to the SSTs in this region (Huang et al, 2003). As there is a cold SST bias in the WNP, the model could underestimate the convection in this region and may further reduce the atmospheric overturning circulations, which can degrade the seasonal predictability in several regions, including East Asia.

Through a correction of the SST bias, we can expect the improvement of seasonal forecasting performance. For example, many CGCMs have systematic

SST biases in tropical Atlantic and surface heat flux is the cause of such bias (Toniazzo and Woolnough, 2014). After diagnosing SST biases, Dippe et al (2019) corrected the surface heat flux and obtained improved hindcast skills. The SST diagnostics presented in this study can also be useful in improving the seasonal prediction skill over WNP in GloSea5.

There is a possibility that the results of the present study can be applied to other CGCMs showing cold SST biases in the WNP. The size of SST biases in GloSea5 is comparable to that in the multiyear simulations of UKESM that share the same model framework. The multi-model mean of historical runs of CMIP5 models also showed a cold bias in the WNP (Wang et al, 2014; Richter, 2015; Wang et al, 2018). If the results of this study are applicable to climate models, we can expect that the biases in climate models can occur during the early stage (seasonal timescale) of the integration. Future research should investigate whether the climate model has a similar pattern of SST error development in the WNP, whether it can be explained by the surface heat flux, and possible approaches to minimize the SST bias.

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