



Tellus A

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The Merits of Ocean Prediction for the Prediction of 2010, 2016, and 2021 Summer Heavy Rainfall Events in Japan

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ABSTRACT

The merits of ocean prediction for heavy rainfall prediction were examined using hindcast experiments for three summer heavy rainfall events in 2010, 2016, and 2021 in Japan. In these events, the rainfall stemmed from Baiu and stationary fronts. The hindcast experiments were conducted using regional atmospheric and coupled models (RUN-ATM and RUN-CPL). The results show that RUN-CPL predicted more accurate rainfall properties than RUN-ATM. RUN-ATM underestimated the accumulated rainfall compared with RUN-CPL, and the underestimation became more significant as the lead time increased. This was due to decreased horizontal vapor transport in the ocean southwest of Japan. Pressure patterns that dominated the vapor transport were different in each case. When an atmospheric model was used, the sea level pressure difference between the Pacific high and Japan was weakened, contributing to weaker vapor transport from the southwest because of the weakened anticyclonic and cyclonic circulations at the region of Pacific high and over Japan. The degraded pressure patterns generated by RUN-ATM stemmed from incorrect latent heat flux response to the sea surface temperature. When air-sea was decoupled in the atmospheric model, the decrease of sea surface temperature by latent heat flux did not occur, so the latent heat flux was overestimated. Also, this caused the decrease in the pressure difference between Pacific high and Japan areas, leading to a weaker moisture transport from the ocean southwest of Japan. The heat budget analysis in the ocean mixed layer suggests that ocean dynamics, especially vertical mixing, contributes to suppress the overestimation of latent heat flux around the Pacific high. It is concluded that heavy rainfall prediction that incorporates appropriate air-sea coupling and ocean prediction provides better results than atmosphere-only model prediction for front-derived heavy rainfall events.

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1 INTRODUCTION

Heavy rainfall is frequently observed during summer in Japan, and the frequency and quantity are increasing because of global warming (Fujibe et al. 2005; Fujibe et al. 2006; Ministry of Education, Culture, Sports, Science and Technology (MEXT) and Japan Meteorology Agency (JMA) 2020). Thus, the socioeconomic impacts are also becoming more significant. Under such circumstances, more accurate weather prediction is required to reduce the risks associated with extreme weather events such as heavy rainfall. Various prediction techniques and systems have been developed to accurately predict heavy rainfall as far in advance as possible (Duc et al. 2021; Ono, Kunii and Honda 2021). However, accurate early prediction still remains difficult since many factors are involved in its occurrence (Kato 2020). To achieve accurate prediction, it is necessary to identify which factors are significant for each event and which should be captured by the prediction model.

During the summer period from June to the middle of July, the Baiu-Meiyu front (Baiu front hereafter) is likely to form as the result of stagnating pressure patterns that form around Japan (Ninomiya and Akiyama 1992; Ninomiya and Shibagaki 2007). The pressure pattern enhances the ingress of warm moisture from southwestern Japan, and this tends to cause favourable atmospheric conditions for heavy rainfall. Severe rainfall is also known to occur when a typhoon enters the front active regions (Takemi and Unuma 2019; Tsuji et al. 2020). Another possible cause of summer heavy rainfall is the atmospheric river (AR), which normally appears with extratropical cyclones (Gimeno et al. 2014; Kamae et al. 2017; Zhu and Newell 1998). The AR is defined as a narrow elongated water vapor flux that induces low-level winds and an abundant moisture supply. When the AR exists over Japan, it creates favourable conditions (e.g., stationary low-level inflow with an abundant moisture supply) for a quasi-stationary band-shaped convection system (QBCS) or “Senjo-Kousuitai”, which causes intense heavy rainfall (Araki et al. 2021; Kato 2020; Yatagai et al. 2019).

The above-mentioned causes of summer heavy rainfall are related to the pressure patterns that dominate incoming warm moist air from the southwestern ocean toward Japan. Thus, to predict heavy rainfall, it is important for the prediction model to predict the pressure patterns around Japan. Some recent studies imply that the sea surface temperature (SST) pattern has a significant impact on the formation of the pressure pattern. Liu et al. (2021) stated that AR-derived rainfall increases due to the SST variability in the region of the Kuroshio extension and causes a difference in the pressure pattern of cyclonic circulation that enhances the vapor transport of AR. Based on this finding, Baba (2022) demonstrated that heavy rainfall prediction was

improved using ocean prediction, focusing on the heavy rainfall event that occurred in July 2020. The study revealed that the AR behaviour was affected by the pressure pattern around Japan, and that both pressure pattern and heavy rainfall could be predicted by a coupled model two weeks in advance. On the other hand, this pressure and rainfall pattern could not be predicted by an atmospheric model. Similar findings were reported by other studies, as the Asian summer monsoon and Meiyu (Baiu) rainfall could not be satisfactorily predicted using only an atmospheric model (Gao et al. 2011; Wang et al. 2005), and the pressure patterns were not satisfactorily reproduced by an atmospheric general circulation model (Nishii, Taguchi and Nakamura 2020).

These results suggest that using a coupled model enables more accurate prediction of heavy rainfall in Japan than a purely atmospheric model. However, the detailed mechanism underlying this difference has not yet been clarified. Also, although the importance of ocean prediction for heavy rainfall prediction in Japan has been discussed with regard to the events of 2020 in Baba (2022), the evaluation is considered insufficient because it was conducted for only one case. Japanese weather prediction has been operated using atmosphere-only models even recently (Japan Meteorological Agency 2019), so if the merits of ocean prediction with the mechanism of the prediction improvements are revealed, the findings will contribute to increase the prediction accuracy of Japanese weather prediction. The purpose of this study is to examine the merits of ocean prediction (i.e., coupled model prediction) with respect to heavy rainfall prediction by conducting hindcast experiments for recent heavy rainfall events. Baba (2022) demonstrated the importance of ocean prediction for the prediction of the 2020 event where AR was dominant. Thus, other heavy rainfall events where AR was not dominant, i.e., Baiu or long-lasting front-derived rainfall events, should be considered. As noted above, AR-dominant heavy rainfall event is caused by extratropical cyclone activity passing near Japan, while the non-AR event is caused by large-scale pressure pattern around Japan. This means that this study focuses on heavy rainfall events which origin and properties of moisture source for heavy rainfall are different from those of the AR-dominant events. In this study, the merits are examined for the prediction of the summer heavy rainfall events that occurred in 2010, 2016, and 2021, in which Baiu and stationary fronts were influential and relatively long-lasting (longer than one week) heavy rainfall appeared in the past 12 years.

The remainder of this paper is structured as follows. In the next Section 2, the model and experimental setup are described, along with the details of the selected heavy rainfall events. Section 3 provides details of the analysis methods used. Results and discussion are presented in Section 4, and summary and conclusions are provided in Section 5.

2 MODEL AND EXPERIMENTAL SETUP

2.1 MODEL DESCRIPTION

The regional atmospheric and coupled models used for this study are identical to those used by Baba (2022). The atmospheric part of the model is based on a nonhydrostatic atmospheric model (Baba et al. 2010) which employs a 30 km horizontal resolution and 34 vertical layers considering 25 km model top height. The atmospheric model employs a convection scheme that can accurately simulate the diurnal cycle of convection (Baba 2019, 2020a), and other various atmospheric variability and mean state (Baba 2020c, 2021; Baba and Ogata 2022; Ogata and Baba 2021). Other parameterizations are identical to those described by Baba (2015, 2019, 2020a). The oceanic part of the model is the Nucleus for European Modelling of the Ocean (NEMO) version 3.6 (Madec and NEMO team 2016), which has a 25 km horizontal resolution and z-coordinate 31 vertical levels. The computational domain for both components was a region in the western north Pacific (105°E–177°W and 6°N–66°N), which is similar to the domain used in the Japan Coastal Ocean Predictability Experiment 2 (JCOPE2, Miyazawa et al. 2009) which output will be used to initialize the present regional coupled model in a future development. The atmospheric and oceanic components were coupled using the Ocean Atmosphere Sea Ice Soil version 3 coupler, Model Coupling Toolkit (OASIS3-MCT, Craig et al. 2017; Valcke 2013). Various fluxes from the atmospheric and oceanic components were exchanged between the components every 30 minutes. Outputs from the atmospheric model were recorded every three hours, and the outputs from the ocean model were recorded every day.

The atmospheric model was configured by replacing the ocean boundary data with prescribed SST data. Adding up fixed SST anomaly at the start date of the hindcast (Table 1) to the daily climatological SST, the SST during the prediction term was fed to the atmospheric model as the surface boundary condition, without using an ocean model. This method is computationally efficient and has been used in ordinary numerical weather predictions (JMA 2019; Zhao, Held and Vecchi 2010). However, the air-sea coupling especially atmospheric feedback on SST is essentially neglected and only SST feedback on the atmosphere is considered by this method (Baba 2022).

This is because the value of SST is prescribed as the boundary data. Hereafter, hindcast experiments using the atmospheric model and coupled model are referred to as RUN-ATM and RUN-CPL, respectively.

2.2 EXPERIMENTAL SETUP

Several recent heavy rainfall events during summer (June, July, and August) in the past 12 years were selected based on their significance as indicated by the disaster reported by the Japan Meteorological Agency (JMA 2022). The selected events mainly originated from front activity, but some cases were excluded from the targeted events. Firstly, very short-term events (shorter than one week) were excluded because the resolution of the prediction model was too coarse to capture such small spatial and short timescale events. Secondly, heavy rainfall events that did not cause heavy rainfall in western Japan (land area west of 138°E) were excluded in order to focus on the typical summer heavy rainfall of Japan (JMA 2022). Finally, the heavy rainfall events that involved typhoon activity were excluded for simplicity to avoid elaborate discussion about typhoon prediction performance. Based on the above conditions, three front-derived heavy rainfall events were selected for the hindcast experiments, as listed in Table 1. These selected events are typical front-derived long lasting heavy rainfall events which are free from the influences of typhoon. In all events, the front active regions existed over center or western Japan, and caused heavy rainfall especially in western Japan area which accumulated rainfall during the period exceeded at least 500 mm. Warm and moist air flowed into over Japan due to the front activity were considered as the main cause of the heavy rainfall for these events. The high accumulated rainfall eventually caused flood damages and sediment disaster in the wide areas of western Japan.

The hindcast experiments were performed from 1–4 days before the start date of the extreme events (i.e., 1, 2, 3 and 4 day lead times were adopted) using time-lagging ensemble members. The start time of each start date was defined as 0, 3, 6, 9, 12, 15, 18, and 21 h, as in Baba (2022). The time-lagging ensemble method is used here because it does not require specific modifications for initial and boundary conditions, and so employing the method is easier than employing the other methods such as perturbation method to generate ensemble members

YEAR	START DATE	END DATE	TERM (DAYS)	HINDCAST TIME (DAYS)	TYPE
2010	Jul 10	Jul 16	7	8–11	Baiu front
2016	Jun 19	Jun 30	12	13–16	Baiu front
2021	Aug 11	Aug 19	9	10–13	Stationary front

Table 1 Selected recent heavy rainfall events based on the JMA reports. Start date and end date indicate the start and end dates of each event. Term is the total number of days each event lasted. Hindcast time is equal to the sum of the lead time and term of each event. Type indicates the main cause of heavy rainfall identified in the JMA reports.

(Molteni et al. 1996). Hereafter, all results are presented by ensemble means which are computed by taking the mean of all time-lagging ensemble members. The results obtained using different lead times (i.e., ensemble mean of time-lagging ensemble members at each lead time) were used to evaluate the influence of lead time on heavy rainfall prediction. The atmospheric conditions were initialised using ERA5 reanalysis data (Hersbach et al. 2020), whereas the ocean conditions were initialised in the initialisation run. The run was performed using ocean conditions initialised by Ocean Reanalysis System 5 (ORAS5, Zuo et al. 2019), together with atmospheric forcing by ERA5 reanalysis data and SST nudging by Optimum Interpolation SST (OISST, Reynolds et al. 2007) for one year before the start date of the hindcast experiments. To exclude uncertainty from the outer-model, the lateral boundary conditions for the atmosphere and ocean were given by the reanalysis data, i.e., daily ERA5 for the atmosphere and monthly ORAS5 for the ocean.

2.3 REANALYSIS AND OBSERVED DATASETS

This study uses several reanalysis and observed datasets to evaluate the hindcast results. Reanalysis based on hourly rainfall with 0.0625° (longitude) $\times$ 0.05° (latitude) horizontal resolution data from mesoscale model (MSM) of JMA (Japan Meteorological Agency 2019) were used to evaluate the daily and 3-hourly rainfall. Daily water vapor, horizontal winds, sea level pressure, and surface heat fluxes were evaluated based on hourly ERA5 reanalysis with 0.25° horizontal resolution. Argo-based gridded datasets (1° horizontal resolution and long-term monthly mean, Hosoda et al. 2010) were used to evaluate the ocean mixed layer depth. The availability of all datasets described here are given in Acknowledgments.

3 ANALYSIS METHOD

3.1 AR DETECTION ALGORITHM

The targeted events mentioned above are considered to have been caused by fronts, but AR activity may have been involved. Therefore, its significance should be investigated. To evaluate the significance of AR-related rainfall, an AR detection algorithm needs to be introduced. AR is frequently identified by vertically Integrated Water Vapor (IWV) or vertically Integrated Vapor Transport (IVT, Gimeno et al. 2014, 2021; Lavers et al. 2012). The IVT is defined as

$$IVT = \sqrt{\left(\frac{1}{g} \int_{1000}^{300} q u dp\right)^2 + \left(\frac{1}{g} \int_{1000}^{300} q v dp\right)^2}, \quad (1)$$

where g is the gravitational acceleration, q is the specific humidity, u and v are horizontal wind velocities and p is pressure (hPa). To exclude seasonal components, the

daily mean climatology of IVT was computed based on 6-hourly ERA5 reanalysis data for 2010–2021. Then the IVT anomaly was computed by subtracting the climatological value from the original IVT value. An AR detection algorithm (Mundhenk, Barnes and Maloney 2016) was applied to the IVT anomaly to detect the AR active region. The AR-related rainfall was identified by linearly interpolating the AR active region onto the rainfall area, and the rainfall where the AR active region overlapped was regarded as AR-related rainfall.

3.2 HEAT BUDGET ANALYSIS FOR THE OCEAN MIXED LAYER

To further analyse the air-sea coupling mechanism in the hindcast experiments from the ocean side, a heat budget analysis for the ocean mixed layer (ML) was introduced. The heat budget analysis follows Moisan and Niiler (1998). The heat budget equation for the ML is given as (Tanizaki et al. 2017; Baba 2020b)

$$\frac{\partial T_{mix}}{\partial t} = \frac{Q_{net} - q_d}{\rho_0 C_p H_{mix}} - \mathbf{u}_{mix} \cdot \nabla T_{mix} - \nabla \cdot (\kappa \nabla T_{mix}) + (vertical), \quad (2)$$

where T_{mix} is the ML temperature (the same as SST), t is the time, $\rho_0 = 1025 \text{ kg m}^{-3}$ is the density of sea water, $C_p = 4186 \text{ J kg}^{-1} \text{ K}^{-1}$ is the specific heat of the sea water, Q_{net} is the net surface heat flux (longwave and shortwave radiative fluxes, and sensible and latent heat fluxes), q_d is the downward penetrated shortwave radiation through the ML, $\mathbf{u}_{mix}$ is the horizontal velocity in the ML, κ is the horizontal diffusion coefficient, and $(vertical)$ is the vertical diabatic term that includes vertical mixing and entrainment. The subscript *mix* indicates that the value is averaged within the ocean mixed layer depth (MLD). Here, the MLD is defined as the depth where the density becomes 0.125 kg m^{-3} higher than that of the surface (Hosoda et al. 2010; Baba 2020b).

4 RESULTS AND DISCUSSION

4.1 ACCUMULATED RAINFALL

Figure 1 compares time variation of daily accumulated rainfall over western Japan (see Figure 1d for the region of western Japan). The comparison between the reanalysis rainfall (Obs), AR-related reanalysis rainfall (Obs-AR), and hindcast results reveals that the accumulated rainfall of the 2016 and 2021 events was not dominated by AR, but AR played a significant role until 14 Jul in the 2010 event. Compared to non-AR case (Figure 1e), when AR-dominated rainfall appears (Figure 1f), extratropical cyclone exists along with the AR and the rich water vapor plume is elongated over Japan. However, the overall patterns of pressure and water vapor in AR-dominated and non-AR cases are similar to each other, as the rich water vapor region exists in the southwest of Japan. It is also apparent that the amount of rainfall has a large

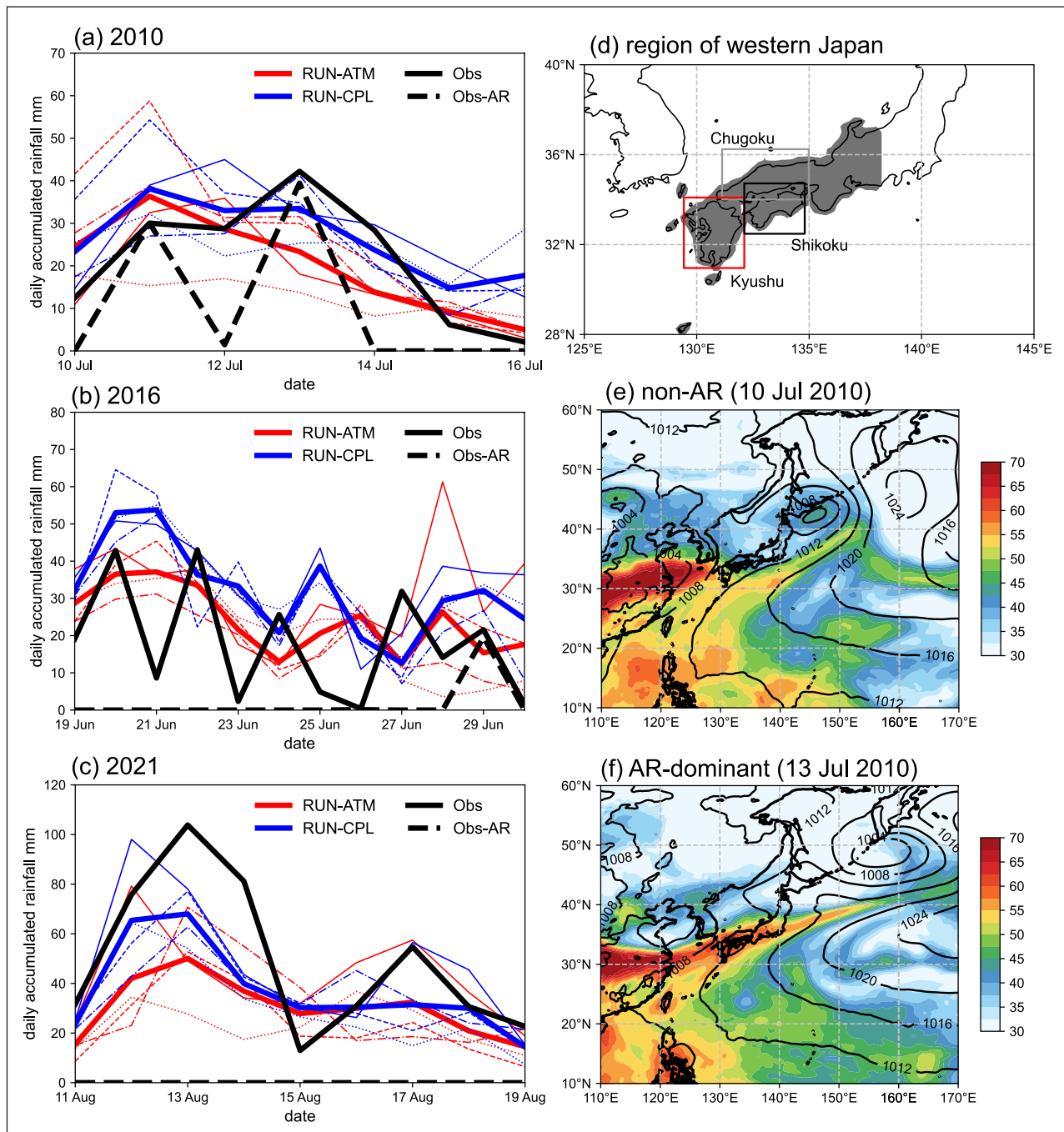


Figure 1 (a), (b), (c): Time variation of daily accumulated rainfall averaged over western Japan during the term of each heavy rainfall event. The thick lines for each case represent ensemble means of each member. The thin solid, dashed, dash-dot, and dotted lines represent 1, 2, 3, and 4 day lead time hindcasts, respectively. The reference reanalysis data (denoted as Obs) were obtained from MSM. Obs-AR represents accumulated rainfall that is related to AR activity. (d): Region of western Japan (land area west of 138°E in the grey shaded region) where the accumulated rainfall was averaged. Kyushu, Shikoku, and Chugoku areas are marked by red, black, and grey colored boxes, respectively. (e), (f): Daily mean column-integrated water vapor (shading, kg m⁻²) and sea level pressure (contour, hPa) from ERA5 for non-AR case (10 Jul) and AR-dominant case (13 Jul) in 2010.

degree of variability between cases, with the 2021 event having the highest rainfall and that of 2010 having the lowest. The rainfall trends are different for each event, but there are several common features. RUN-CPL predicted larger rainfall than RUN-ATM, regardless of the event. In addition, as the lead time became longer, both RUN-ATM and RUN-CPL predicted smaller rainfall, and this decrease was much greater for RUN-ATM than for RUN-CPL. AR played a significant role in

the 2010 event, but the above features that originated from differences in the prediction model were similar for all events. Therefore, there must be a mechanism that causes the underestimated accumulated rainfall for the atmosphere-only model, regardless of the rainfall type.

The distributions of the observed and predicted accumulated rainfall are compared in Figure 2. A large accumulated rainfall was recorded in the Kyushu area for all events. RUN-CPL predicted qualitatively similar

accumulated rainfall patterns over the land compared with the reanalysis, although the ensemble mean of this case indicates overestimation of rainfall in some regions (e.g., southeastern Kyushu area in 2010, and Shikoku and Chugoku areas in 2016, see also Figure 1d). RUN-ATM predicted partially similar accumulated rainfall patterns to RUN-CPL, but as presented in Figure 1, RUN-ATM predicted smaller rainfall than RUN-CPL, and these apparent differences appeared for the

Kyushu area (fourth column in Figure 2). This means that RUN-ATM underestimated rainfall compared with RUN-CPL for all events, and the phenomenon appears to be especially in the Kyushu area. Thus, there must be a mechanism that degrades the prediction of RUN-ATM for the Kyushu area.

Forecast skills for the present hindcast experiments were evaluated using forecast diagnostics for all events (Figure 3). Threat score (TS), probability of detection

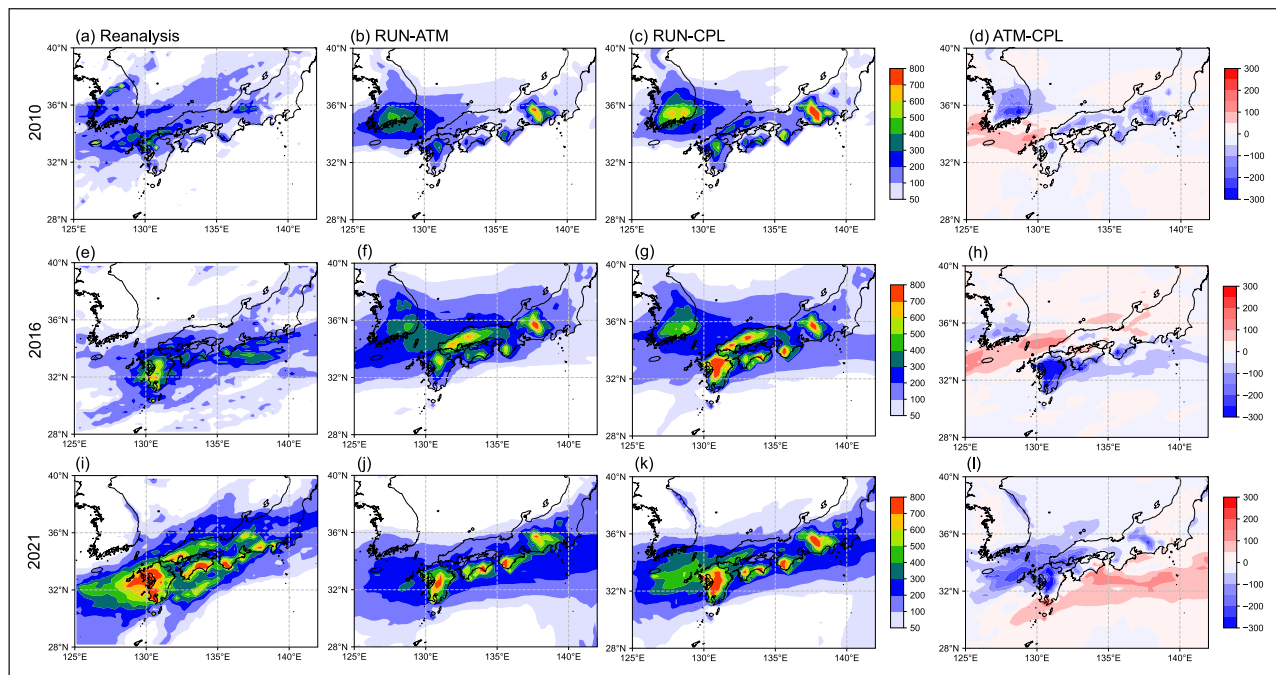


Figure 2 Distributions of accumulated rainfall (mm) during the term of each heavy rainfall event. (a), (e), (i): Reanalysis (MSM), (b), (f), (j): accumulated rainfall in RUN-ATM, (c), (g), (k): accumulated rainfall in RUN-CPL, and (d), (h), (l): differences of accumulated rainfall between RUN-ATM and RUN-CPL. Hindcast results are given as ensemble means, and the ensemble means were computed using hindcast with 1–2 day lead time. Each row represents a different heavy rainfall event.

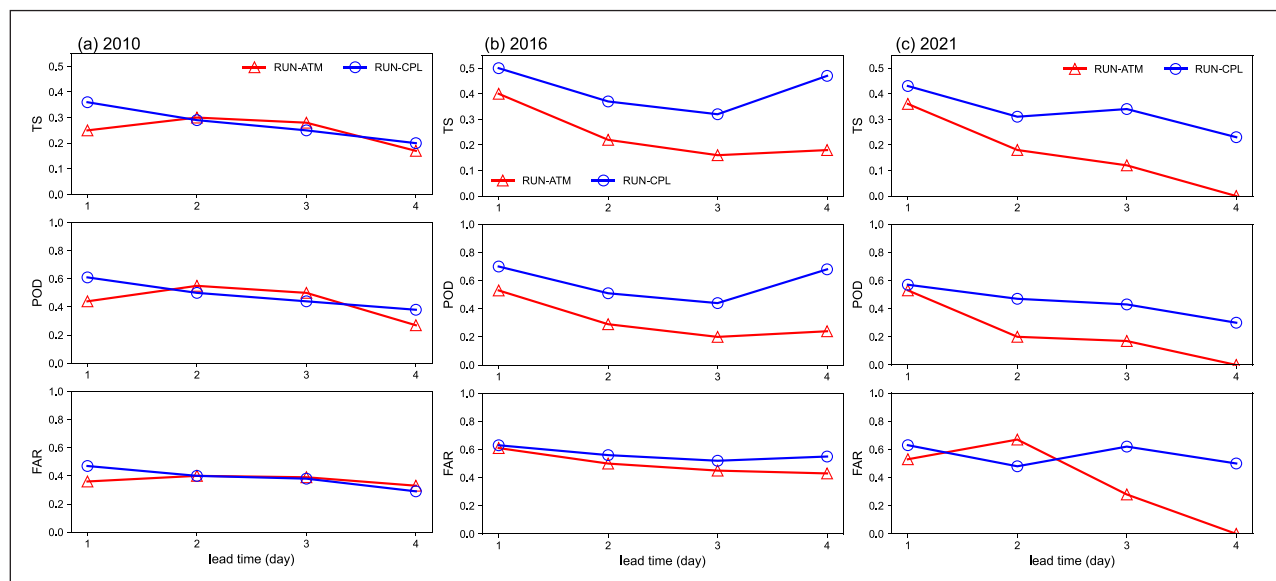


Figure 3 Threat score (TS), probability of detection (POD), and false alarm rate (FAR) of hindcast experiments for heavy rainfall over Kyushu area. Each score is calculated for heavy rainfall exceeding 5 mm h^{-1} in (a) 2010 and (b) 2016, and heavy rainfall exceeding 10 mm h^{-1} in 2021. Note that weaker rainfall intensity was used for 2010 and 2016 events, since the rainfall intensity of these cases were weaker than that of 2021 event. The 3-hourly rainfall data from the reanalysis and hindcast experiments were used to compute the statistical values.

(POD), and false alarm rate (FAR) (e.g., Wilks 2006) were estimated for heavy rainfall over the Kyushu area. The scores are estimated for rainfall exceeding 5 mm h^{-1} in 2010 and 2016, and for rainfall exceeding 10 mm h^{-1} in 2021. It is found that RUN-CPL indicate higher TS and POD than RUN-ATM for all events although they are slightly worse than RUN-ATM for 2–3 day lead time in 2010, meaning that RUN-CPL better captured the heavy rainfall occurrence at the correct timing than RUN-ATM. Although FAR of RUN-CPL is higher than that of RUN-ATM in longer lead time, the value does not further increase. These facts mean that overall forecast skill of RUN-CPL for heavy rainfall in the region is superior to that of RUN-ATM.

4.2 HORIZONTAL VAPOR TRANSPORT

To investigate the moisture properties that caused heavy rainfall in these events, IWV is analyzed as in Baba (2022) (Figure 4). Regardless of the event, abundant moisture was supplied from the ocean region southwest of Japan. All cases successfully predicted IWV patterns for the heavy rainfall events, which are qualitatively similar to

the reanalysis data. However, the wind velocity patterns along with the anticyclonic circulation due to the Pacific high ($140^{\circ}\text{--}170^{\circ}\text{E}$ and $20^{\circ}\text{--}40^{\circ}\text{N}$) were different for each prediction model. The reanalysis data shows that the anticyclonic circulation reached the ocean region south of Japan ($130^{\circ}\text{--}140^{\circ}\text{E}$ and around 30°N), but RUN-ATM failed to predict this feature except for the 2016 event. On the other hand, RUN-CPL successfully predicted this feature for all events. Further analyses are conducted for IWV difference (Figure 5). Both cases overestimated IWV at the region of Pacific high compared with the reanalysis, but RUN-CPL seems to suppress the overestimation. In addition, RUN-ATM underestimated IWV over the southwestern part of Japan for all cases. Taking difference in IWV between RUN-ATM and RUN-CPL (third column of Figure 5), it is clearly shown that the overestimation of IWV at Pacific high and the underestimation of IWV over southwestern Japan are common for all events, and are more significant in RUN-ATM than in RUN-CPL. Considering these features, moisture flux coming from southwest of Japan is influenced by both differences in low-level winds and IWV.

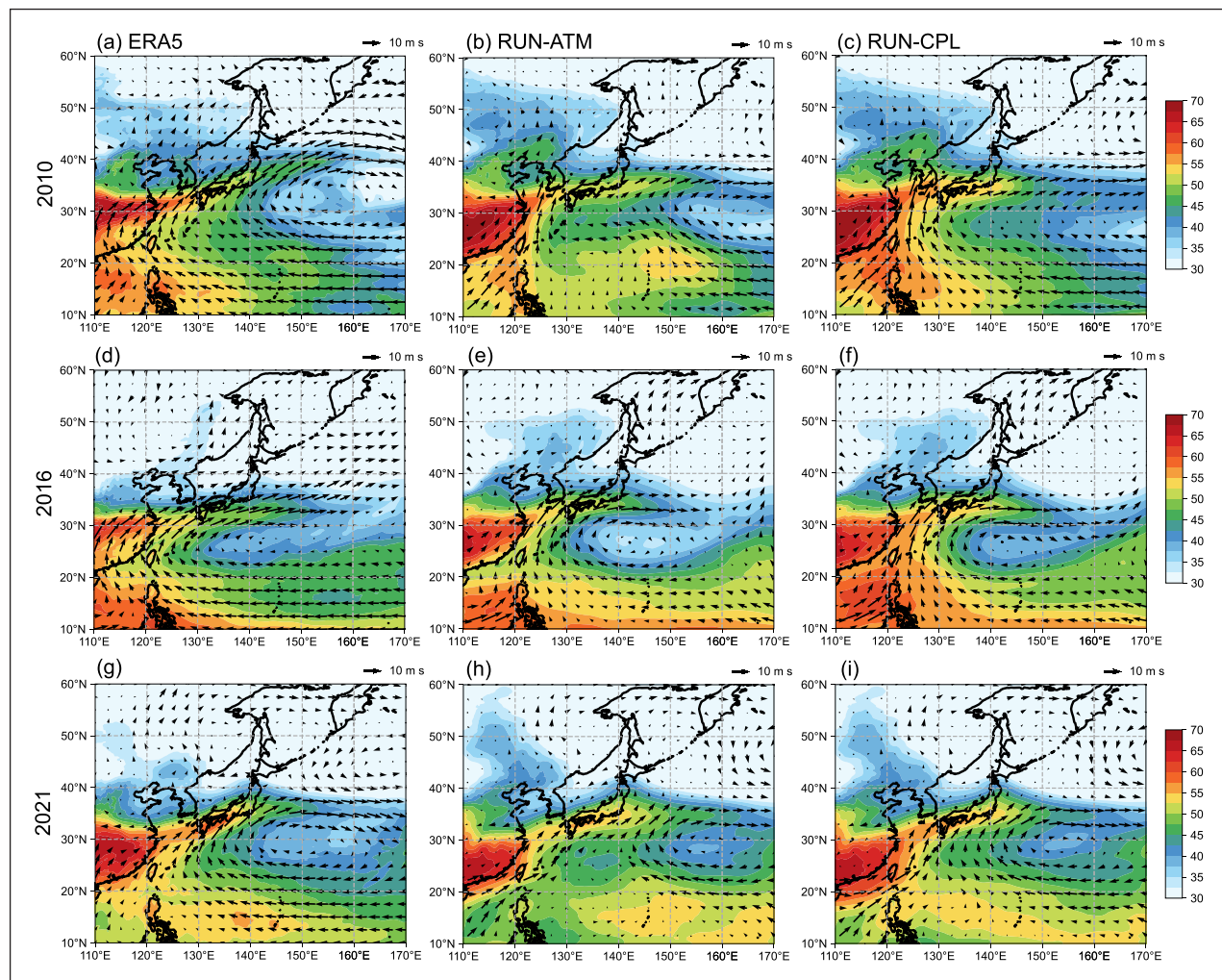


Figure 4 Distributions of IWV during the heavy rainfall events. The shading and vectors indicate IWV (kg m^{-2}) and wind velocity at 850 hPa level (m s^{-1}), respectively. IWV and wind velocity are time-averaged across the term of each event, and the hindcast results are presented by averaging ensemble means of hindcast with 1–4 day lead time. The first, second, and third columns respectively represent the reanalysis (ERA5), RUN-ATM, and RUN-CPL, and each row represents a different heavy rainfall event.

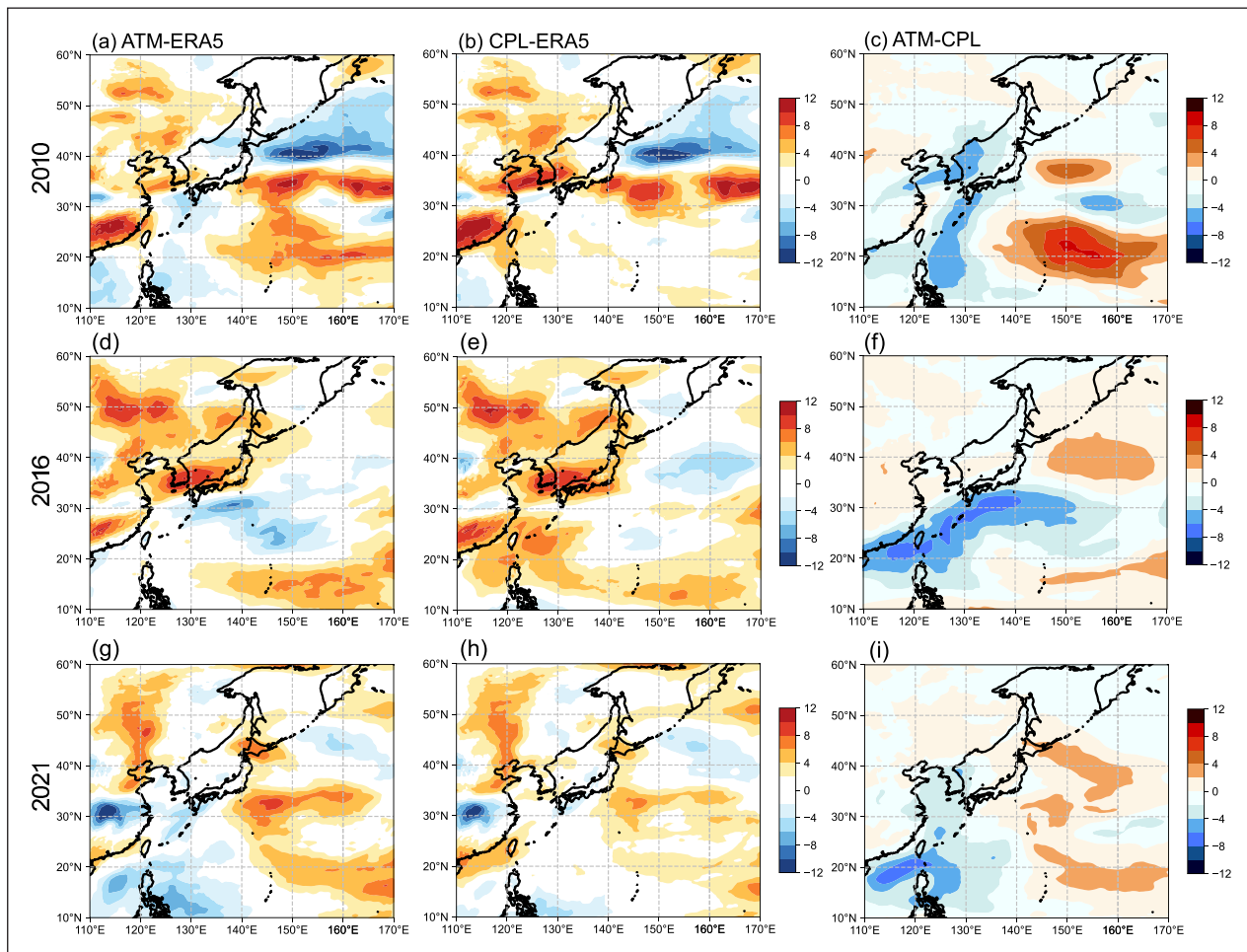


Figure 5 Distributions of difference in the time-averaged IWP (kg m^{-2}) shown in Figure 4. **(a), (d), (g)**: Difference in the IWP between RUN-ATM and ERA5, **(b), (e), (h)**: difference in the IWP between RUN-CPL and ERA5, and **(c), (f), (i)**: difference in the IWP between RUN-ATM and RUN-CTL.

The IVT was next used to analyse the horizontal vapor transport of the events, instead of applying the AR detection algorithm. The reason for this is that horizontal moisture transport measured by IVT is useful for identifying conditions that are favourable for heavy rainfall, which is frequently caused by the abundant moisture coming from the southwest of Japan by southwesterly wind (Kato 2020). IVT and the impacts of lead time are compared in Figure 6. In all cases, strong IVT was observed over the southwestern and southeastern regions of Japan. Focusing on the IVT difference due to lead time, IVT decreases over Japan as the lead time increases (shading in the first and second columns in Figure 6), while the IVT in the ocean southwest of Japan increases as the lead time increase except for 2016, indicating that IVT tends to decrease over the western Japan while it increases in the ocean region as the lead time increase. In 2016, the IVT decreases not only over Japan and but also in the southwest of Japan as the lead time increase. The decrease of IVT seen near Japan is greater for RUN-ATM than for RUN-CPL. This implies that the predicted pressure patterns are assumed to be different for each case, and are degraded more in RUN-ATM than in RUN-

CPL with lead time increase, since the pressure patterns determine the winds around Japan.

The IVT differences due to the prediction model with a same lead time show that RUN-ATM predicted smaller IVT than RUN-CPL in the ocean regions southwest and south of Japan (third column in Figure 6). These correspond to the regions where rich precipitable water is frequently supplied during the heavy rainfall events in Japan (e.g., Araki et al. 2021; Baba 2022; Takemi and Unuma 2019). Also, a part of this region overlaps with the Kyushu area, where RUN-ATM predicted smaller accumulated rainfall (Figure 2), and different low-level winds (Figure 4) and IWP (Figure 5) compared with RUN-CPL.

4.3 PRESSURE PATTERNS

The sea level pressure (SLP) patterns are compared in Figure 7 in the same fashion as for IVT. In all cases, the SLP patterns of Pacific high appear in the ocean region southeast of Japan. Comparing the SLP of the Pacific high for different lead times (first and second columns in Figure 7), it was found that the SLP decreases as the lead time increases. In addition, the decrease is larger for RUN-ATM than for RUN-CPL, meaning that the Pacific high tends to be weakened in atmospheric model

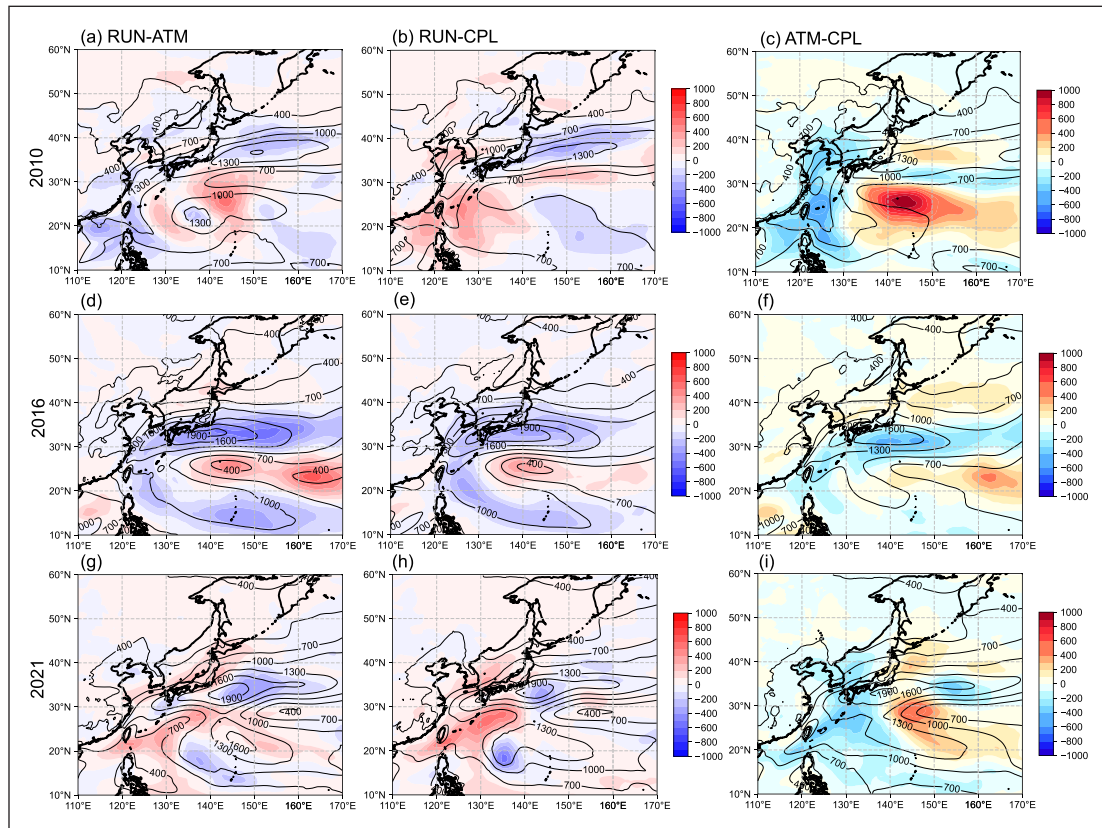


Figure 6 Distributions of IVT ($\text{kg m}^{-1} \text{s}^{-1}$) during each heavy rainfall event by the lead time and cases. (a), (b), (d), (e), (g), (h): IVT (contour line) is for each case (mean of 3–4 day lead time), the IVT differences (shading) were calculated as the mean of 3–4 day minus the mean of 1–2 day lead time, and (c), (f), (i): IVT predicted by RUN-CPL (contour line, mean of 1–2 day lead time), and IVT differences calculated from RUN-ATM minus RUN-CPL (shading, mean of 1–2 day lead time).

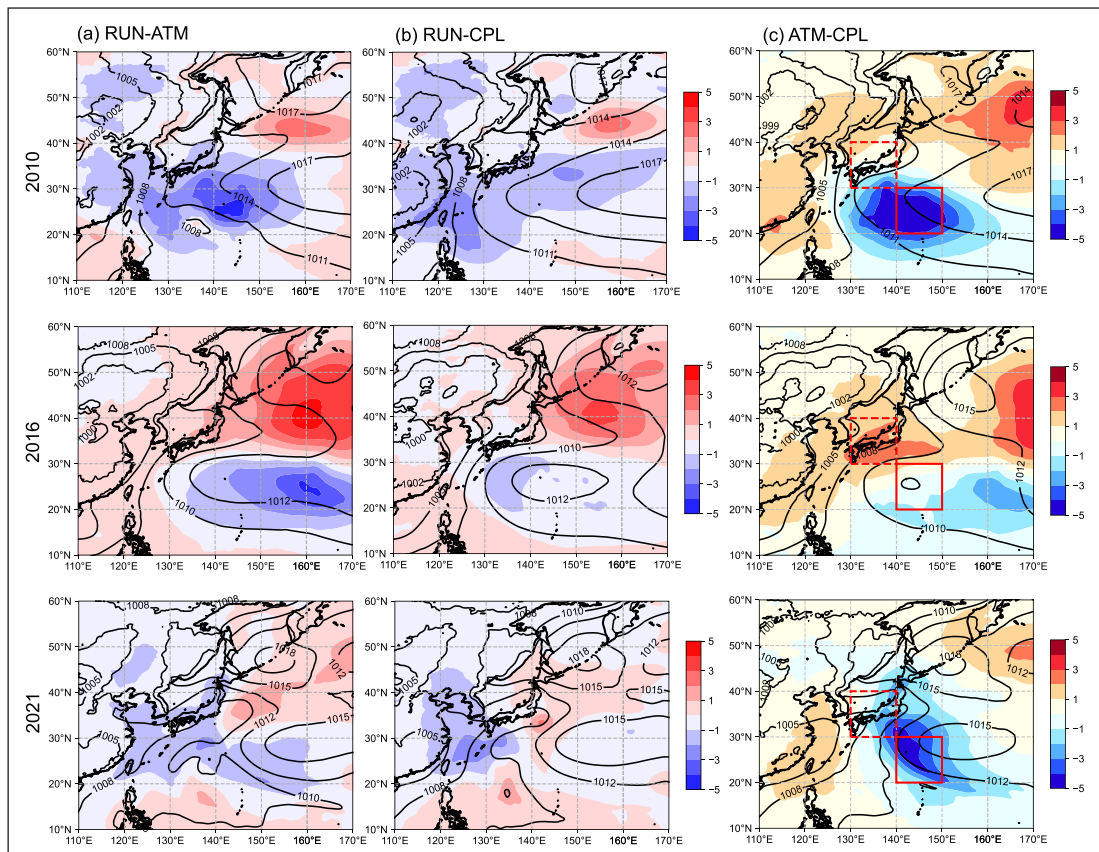


Figure 7 As Figure 6 but for sea level pressure (hPa). Red colored solid box and red colored dashed box indicate area A (140° – 150° E and 20° – 30° N) and area B (130° – 140° E and 30° – 40° N), respectively.

prediction. This decreased SLP in RUN-ATM at the Pacific high is apparent in the comparison of the prediction model with a same lead time (third column in Figure 7). The comparison also suggests that RUN-ATM predicted higher SLP than RUN-CPL over Japan (not at the Pacific high) for the 2010 and 2016 events.

To analyze the time variation of SLP at Pacific high, the time variations of area-averaged SLP are compared in Figure 8 (first column). Here, the area of the Pacific high is defined as 140°–150°E and 20°–30°N (area A, see the location in Figure 7). It is apparent that RUN-CPL predicted SLP closer to the reanalysis than did RUN-ATM for the 2010 and 2021 events. However, RUN-CPL failed to predict SLP as accurately for the 2016 event, performing similar to RUN-ATM. This fact implies that the successful prediction of the Pacific high is not the only relevant factor for the superior RUN-CPL prediction. As

presented in Figure 7, RUN-ATM predicted a higher SLP over the island of Japan, and so the pressure pattern difference between the area A and this region could be another reason for the better rainfall prediction. To see the SLP difference between the area of the Pacific high and the area over the island, the time variation of the area-averaged SLP difference was analysed (second column of Figure 8). The island area was defined as 130°–140°E and 30°–40°N (area B, see the location in Figure 7). The area-averaged SLP difference of RUN-CPL appears to be closer to the observation than that of RUN-ATM for all events as presented by the root-mean-square error (RMSE) of SLP difference in Figure 8. In 2016, the RMSE of RUN-CPL is slightly larger than that of RUN-ATM, but the RMSE is smaller than RUN-ATM when the last 2 days after the peak of SLP difference are excluded, as the RMSEs are 2.9 and 2.4 for RUN-ATM and RUN-CPL, respectively. In

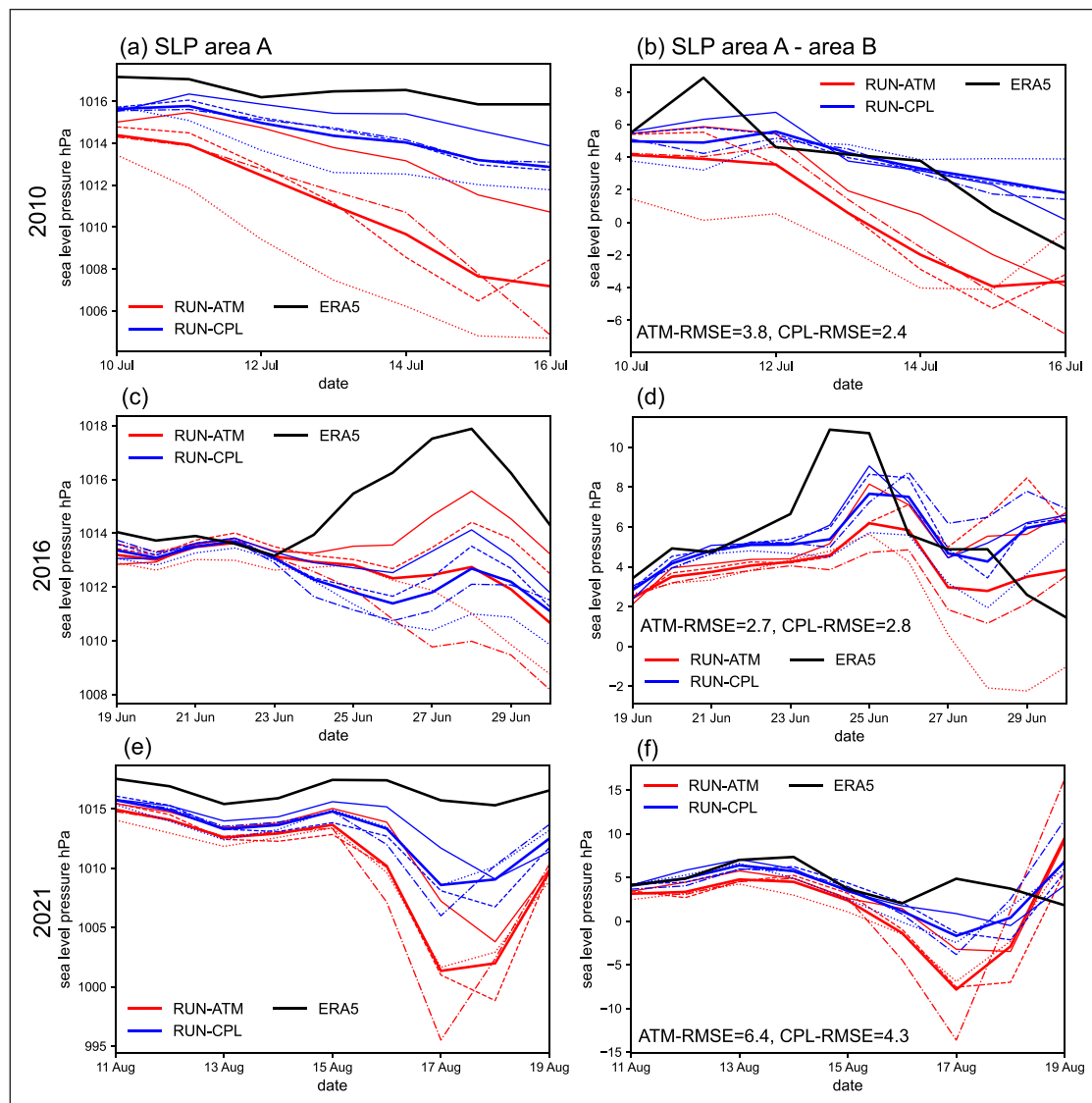


Figure 8 Time variations of area-averaged SLP and SLP difference for each heavy rainfall event. (a), (c), (e): Time variation of SLP averaged for area A. (b), (d), (f): Time variations of SLP difference between area A and area B. The solid, dashed, dash-dot, and dotted lines represent hindcast of 1, 2, 3, and 4 day lead time, respectively. Each row corresponds to a different heavy rainfall event. ATM-RMSE and CPL-RMSE in the right column figures represent root-mean-square error of SLP difference for each hindcast case compared with the SLP difference of ERA5.

light of this, the SLP difference could play the following important role. When the difference in SLP between the areas A and B is sufficiently large, anticyclonic circulation at the Pacific high and cyclonic circulation over the island of Japan are enhanced, leading to larger IVT in the southwestern ocean region moving toward the area of Japan, and resulting in a large accumulated rainfall. Thus, when the SLP difference is small, the IVT also becomes small and this results in an underestimated accumulated rainfall.

These hypotheses are confirmed from the relationship between SLP difference, IVT difference, and pressure gradient force due to the SLP difference (Figure 9). When

SLP is unrealistically lower at Pacific high and it is higher over Japan, direction of pressure gradient force becomes from Japan toward the region of Pacific high. The lower SLP forms convergent force at Pacific high. This feature corresponds well to the IVT differences, since lower SLP increases IVT over Pacific high by a convergence of moisture flux. The pressure gradient force due to the SLP difference also indicates that the force from Japan to Pacific high is enhanced, when SLP pattern is wrong as predicted in RUN-ATM (Figure 9a). With the influence of Coriolis force in the northern hemisphere, the wrong pressure gradient force enhances anticyclonic circulation in the southwest of Japan. In addition, lower SLP at

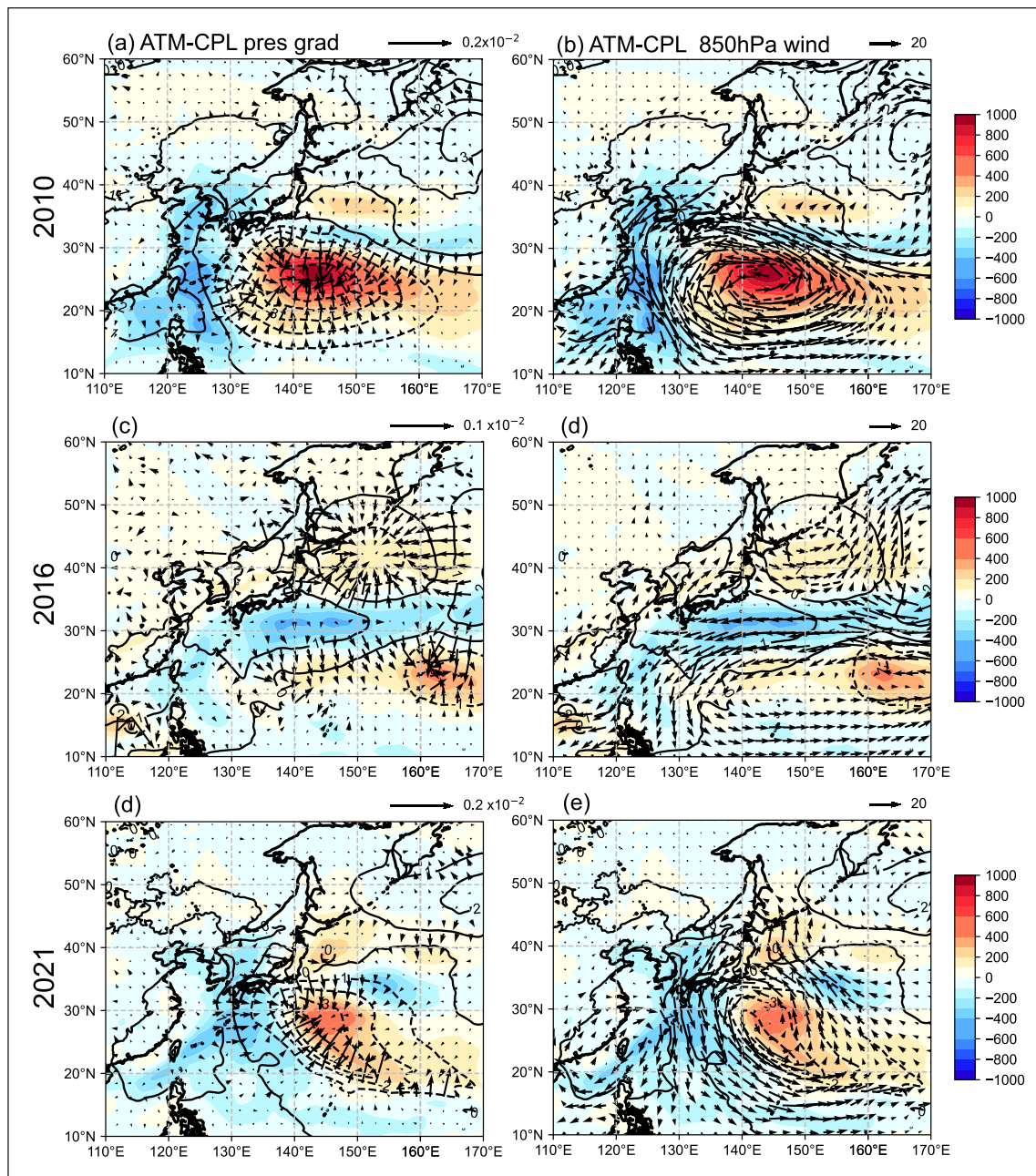


Figure 9 Comparison of SLP difference (contour line, hPa, 1 hPa interval), and IVT difference (shading, kg m⁻¹ s⁻¹), pressure gradient force (vector in left column, Pa m⁻¹) estimated from the SLP difference, and horizontal wind difference at 850 hPa (vector in right column, m s⁻¹). Differences in SLP and IVT are defined by RUN-ATM minus RUN-CPL, and are common for left and right column figures. Results of time-averaged hindcast of 1–2 day lead time during the each event are used to compute the differences.

Pacific high enhances cyclonic circulation (Figure 9b). As the result, wrong pressure pattern in RUN-ATM enhances northeasterly winds that weakens southwesterly winds from the southwest of Japan, compared to RUN-CPL. These facts mean that SLP difference between over Japan and Pacific high should be predicted so that the SLP difference appears to be large, in order to predict sufficiently large IVT coming from southwest of Japan.

4.4 SURFACE HEAT FLUX OVER THE OCEAN

The pressure pattern difference was found to result in different rainfall prediction from the above analyses; however, which factor caused the pressure pattern difference remains unknown. During summer around Japan, the atmospheric feedback to SST is known to be significant (Wang et al. 2005), and so air-sea coupling should be factored into rainfall prediction. Otherwise, if only SST feedback to the atmosphere is considered, the prediction error could be significant. Indeed, Baba (2022) showed that latent heat flux from the ocean tends to be overestimated by a purely atmospheric model due to this incorrect feedback, and this was found to be the main cause of the incorrect pressure patterns associated with the Pacific high.

To check whether the incorrect pressure patterns are derived from the latent heat flux in the events under investigation, the area-averaged surface heat fluxes are

compared in Figure 10. As indicated by the comparison, the latent heat flux is the most dominant among the various heat fluxes from the ocean. This fact is consistent with the finding of Baba (2022), although the causes of the heavy rainfall are different. Due to this, the heat flux difference between the examined cases is the largest for the latent heat flux. In all events, RUN-ATM overestimated the latent heat flux in the region of the Pacific high, and the overestimation became more significant in the later prediction time. On the other hand, RUN-CPL suppressed the overestimation, and even underestimated the latent heat flux for the 2010 event.

The distributions of latent heat flux and SLP patterns for the reanalysis and hindcast results are compared in Figure 11. RUN-ATM appears to have overestimated latent heat flux in the region of the Pacific high for the 2010 and 2021 events compared with the reanalysis and RUN-CPL. In 2016, RUN-ATM predicted lower latent heat flux in lower latitude (10° – 20° N). However, focusing on the latent heat flux at area A, RUN-ATM also overestimated the flux compared to RUN-CTL. The overestimated latent heat flux means that SST feedback to the atmosphere is significant, leading to enhanced convection and thus lower SLP. Indeed, SLP at the Pacific high in RUN-ATM for these events is weaker than the reanalysis and the RUN-CPL prediction, except for 2016 event.

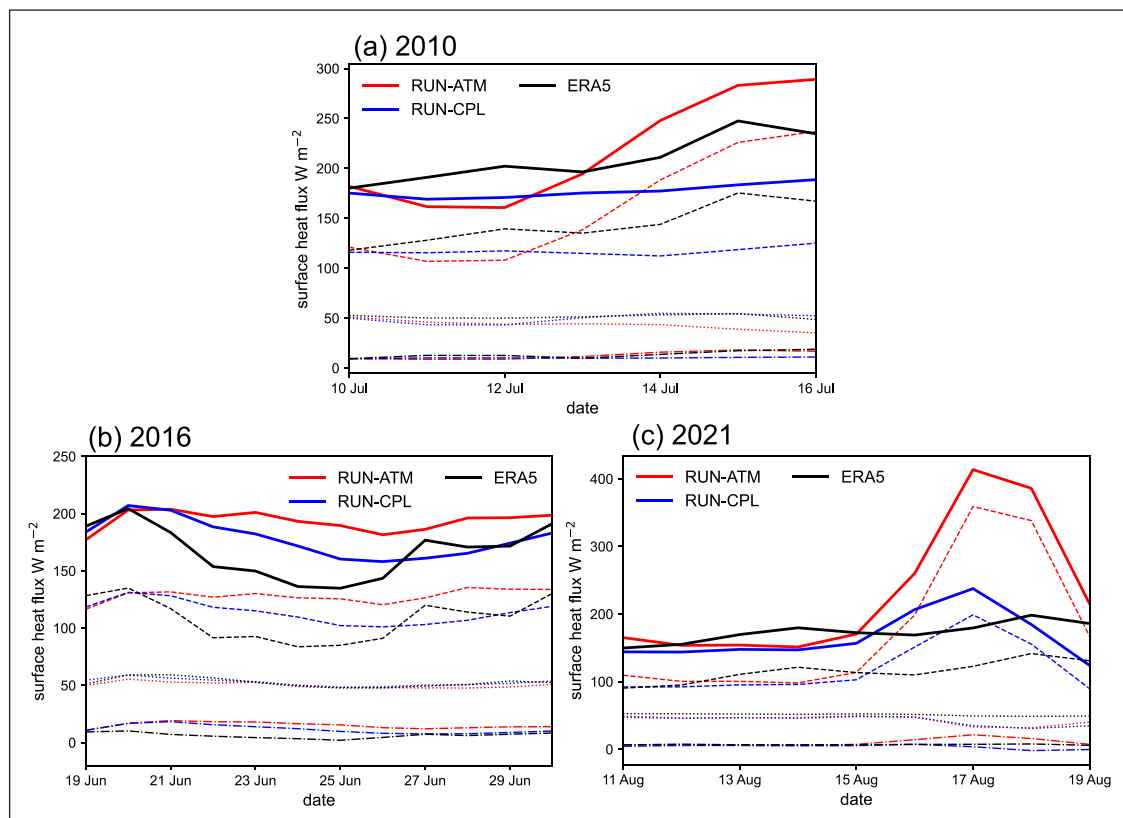


Figure 10 Time variation of various area-averaged surface heat fluxes. The solid, dashed, dash-dot, and dotted lines represent total heat flux, latent heat flux, sensible heat flux, and surface net thermal radiation, respectively. The surface heat fluxes are area-averaged for the area A and are given by the means of hindcast with 1–4 day lead time.

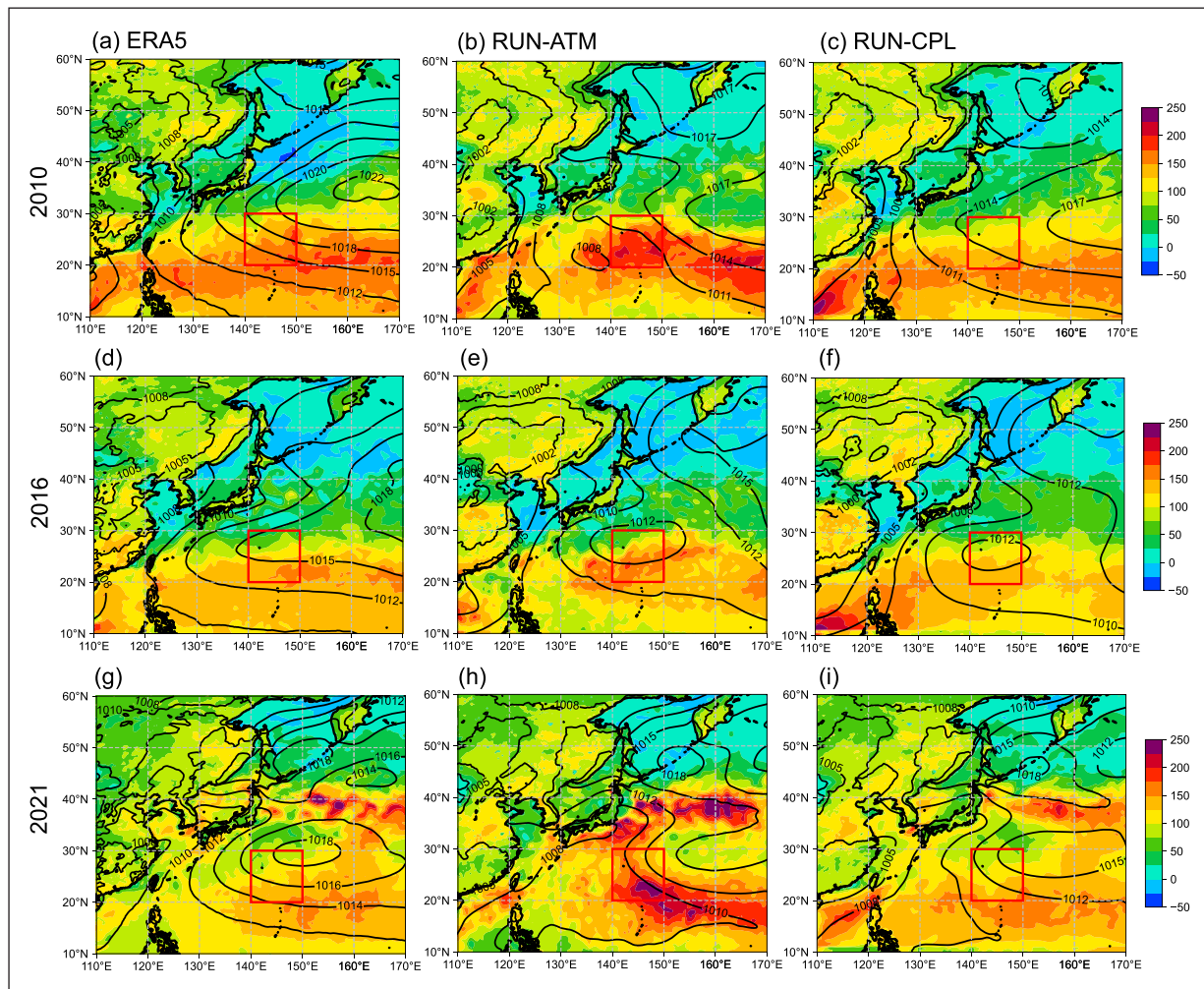


Figure 11 Distributions of time-averaged latent heat flux (shading, W m^{-2}) and SLP (contour lines, hPa). Each variable was time-averaged over the term of each event, and the hindcast is given by the means of hindcast with 1–4 day lead time. The first, second, and third columns respectively represent the distributions of reanalysis (ERA5), RUN-ATM, and RUN-CPL, and each row represents a different heavy rainfall event. The region of area A is marked by red colored boxes.

Figure 12 shows a comparison of the latent heat flux differences between RUN-ATM and RUN-CPL along with the SLP differences. In both the 2010 and 2021 events, decreased SLP in RUN-ATM at the Pacific high strongly corresponds to the overestimated latent heat flux (Figure 12a and 12g). This supports the aforementioned mechanism, i.e., that the absence of air-sea coupling generated an incorrect latent heat flux response, resulting in an unrealistic lower SLP. RUN-CPL slightly overestimated latent heat flux at the Pacific high but it is less significant than that in RUN-ATM, so SLP decrease is suppressed (Figure 12b and 12h). Comparing with RUN-CPL, a relatively low latent heat flux of RUN-ATM was observed in the 10° – 20°N and 110° – 120°E regions (South China Sea), where the SST decreased from that of the start date. This feature is observed in all events, but is the most significant in 2016 (Figure 12d and 12f). The region of low latent heat flux corresponds to a high IWP region (Figure 4) and also a high SLP region. These atmospheric properties were caused by the influence of SST feedback. When positive-only SST feedback is considered in the model, SST decrease (increase) enhances SLP increase

(decrease) there, through suppressed (enhanced) latent heat flux and resulting convection. Therefore, the SST decrease is considered to cause the higher SLP in the South China Sea. The relatively high-pressure atmosphere in RUN-ATM is thus considered to extend toward Japan area from southwestern Japan, through the transport due to southwesterly winds which are caused by the anticyclone circulation around Pacific high (Ninomiya and Shibagaki 2007). As noted above, this higher SLP decreased the SLP difference between the area over the Japan side and the Pacific high in 2016, leading to weaker IVT, and a reduction in the accumulated rainfall in Japan. RUN-CPL underestimated SLP at Pacific high in 2016, but SLP did not increase as RUN-ATM over Japan area, so SLP difference between Japan and Pacific high was kept to be large.

4.5 OCEAN MIXED LAYER

It was found that the coupled model could better predict the heavy rainfall events by predicting better pressure patterns. However, change in the ocean conditions during the events, especially the heat budget remains

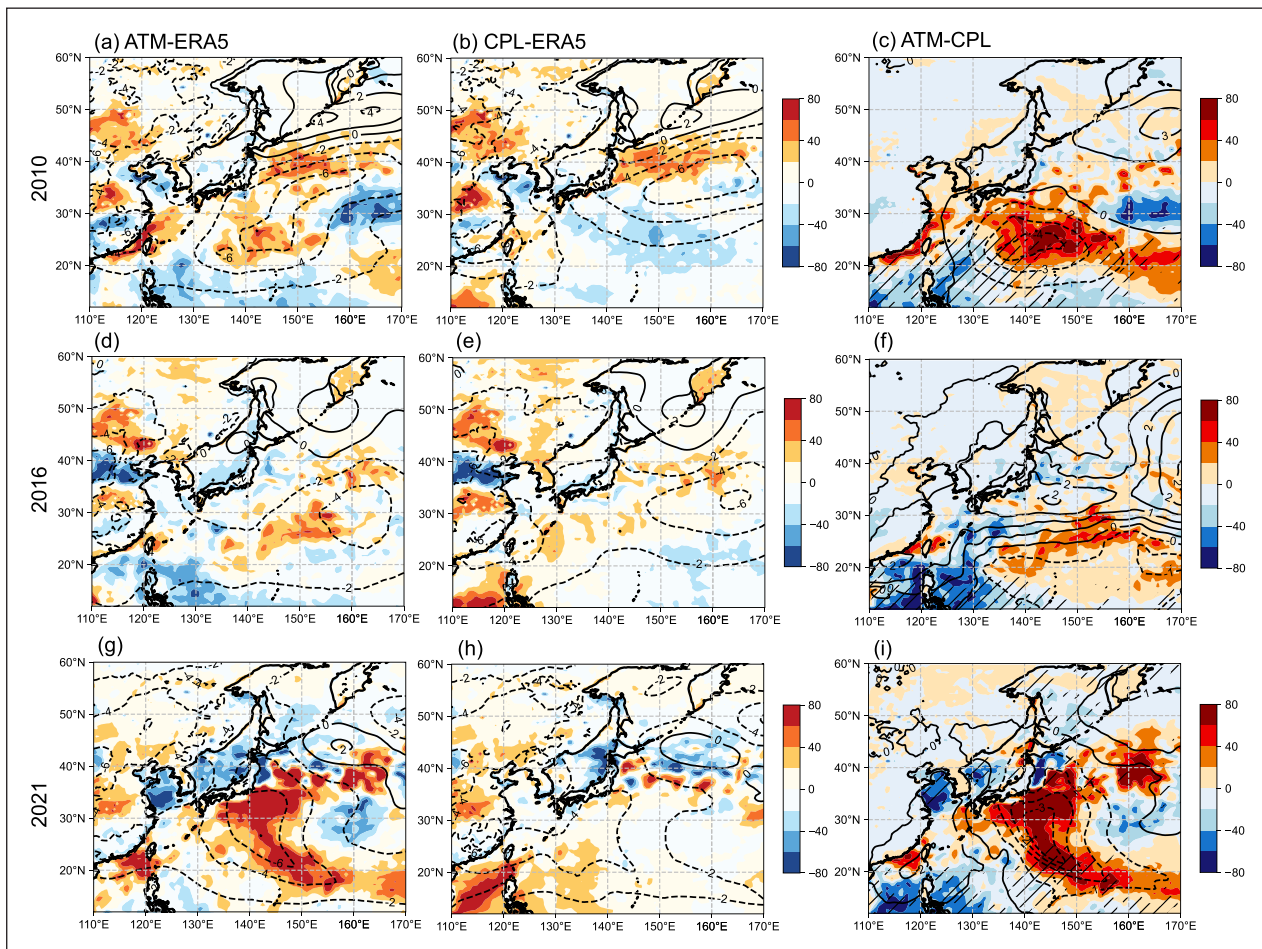


Figure 12 (a), (d), (g): Differences in the latent heat flux (shading, W m^{-2}) and SLP (contour lines, hPa) between RUN-ATM and ERA5. **(b), (e), (h):** As (a), (d), (g) but for differences between RUN-CPL and ERA5. **(c), (f), (i):** As (a), (d), (g) but for differences between RUN-ATM and RUN-CPL. The hatching indicates the region where the prescribed SST decreased from the start date of the hindcast for RUN-ATM prediction.

unknown, and it has not yet been analyzed. If the heat budget change occurred through processes other than the heat exchange with the atmosphere, a slab ocean model (SOM, Kiehl et al. 2006), which only partly simulates the air-sea coupling in an atmospheric model, may be insufficient to satisfactorily predict heavy rainfall. Such a result also suggests that the inclusion of ocean prediction is inevitable to accurately predict summer heavy rainfall in Japan.

To investigate the heat budget in the ocean together with air-sea coupling, heat budget analysis within the ocean mixed layer (ML) was conducted. Before analysing the heat budget, the predicted MLD was compared with the observed values (Hosoda et al. 2010), as shown in Figure 13. The hindcast results predicted quantitatively similar MLD to the observed. During the summer season, the MLD tends to become thinner than other seasons. In particular, the MLD at the Pacific high is much thinner than that in other regions and approaches 20 m (Figure 13g). This implies that the ML temperature at the Pacific high is easily influenced by atmospheric variability. It was also found that the MLD and its distribution have case-dependent variability with respect to the climatology of MLD. For example, the 2021 event showed a deeper

MLD than the climatology near the island of Japan. Since the SOM normally prescribes MLD based on the climatology (Kiehl et al. 2006), it cannot take into account this variability, which may lead to an erroneous heat budget.

In air-sea coupling, the ML temperature decreases due to heat loss mainly by the latent heat flux. However, the contribution of other processes such as ocean dynamics to the ML temperature remains unknown. To answer this question, the ML temperature tendencies were computed and compared for each event (Figure 14). The overall tendencies in all cases were positive at the Pacific high except for its surrounding area, meaning that heat loss by the latent heat flux was balanced with other processes. Focusing on the tendencies by ocean dynamics (second and third columns of Figure 14), both negative and positive tendencies appear. The negative tendency mostly originates from vertical processes (especially vertical mixing), whereas the positive tendency originates from horizontal processes (horizontal advection and diffusion). The negative tendency by the vertical processes presents non-negligible impacts on the total tendency, especially in the 2021 event. The sum of surface incoming and outgoing heat fluxes is

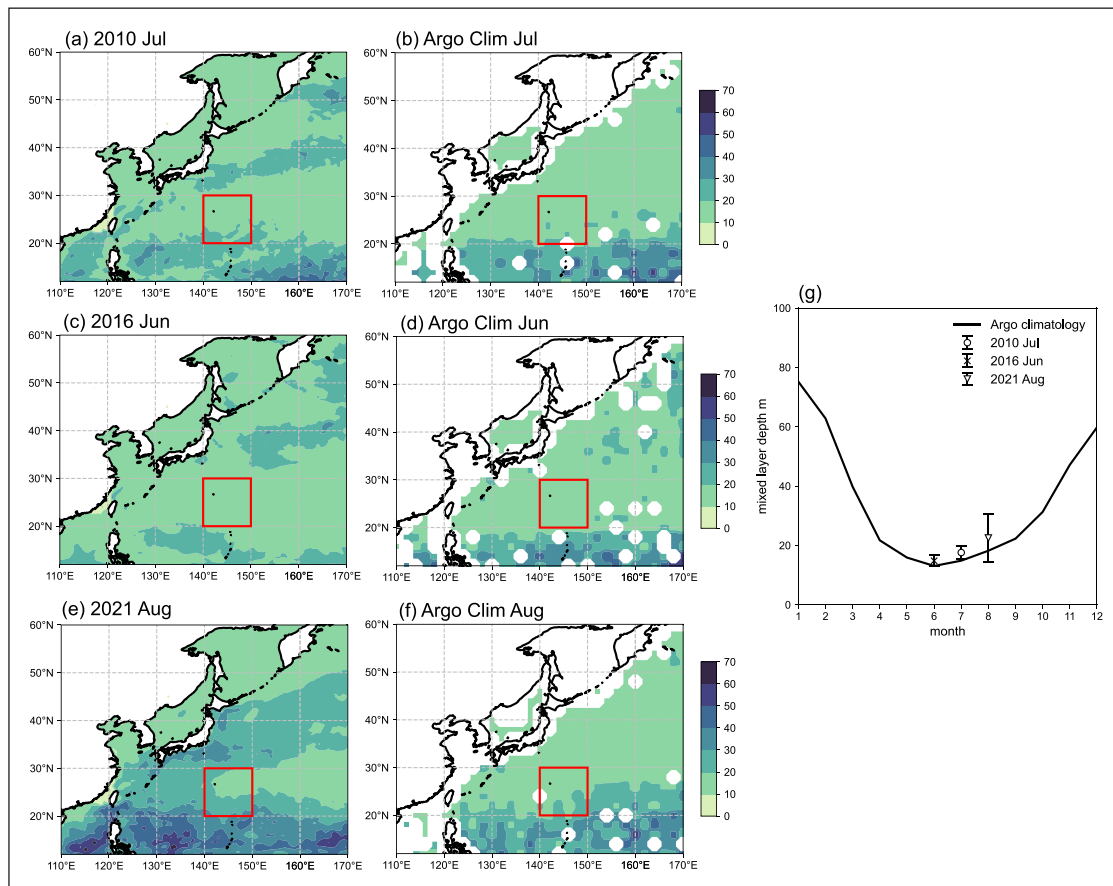


Figure 13 Time-averaged distributions of predicted MLD (m) in the heavy rainfall events with the corresponding observed climatological MLD. (a): RUN-CPL in Jul 2010, (b): Argo Jul climatology, (c): RUN-CPL in Jun 2016, (d): Argo Jun climatology, (e): RUN-CPL in Aug 2021, and (f): Argo Aug climatology. (g): Comparison of area-averaged (area A, marked by red colored boxes) MLD and climatological MLD (the error bars represent 1.5 standard deviations). The MLD distributions are time-averaged for the term of each event. Argo-derived observational data (Hosoda et al. 2010) were used as the reference.

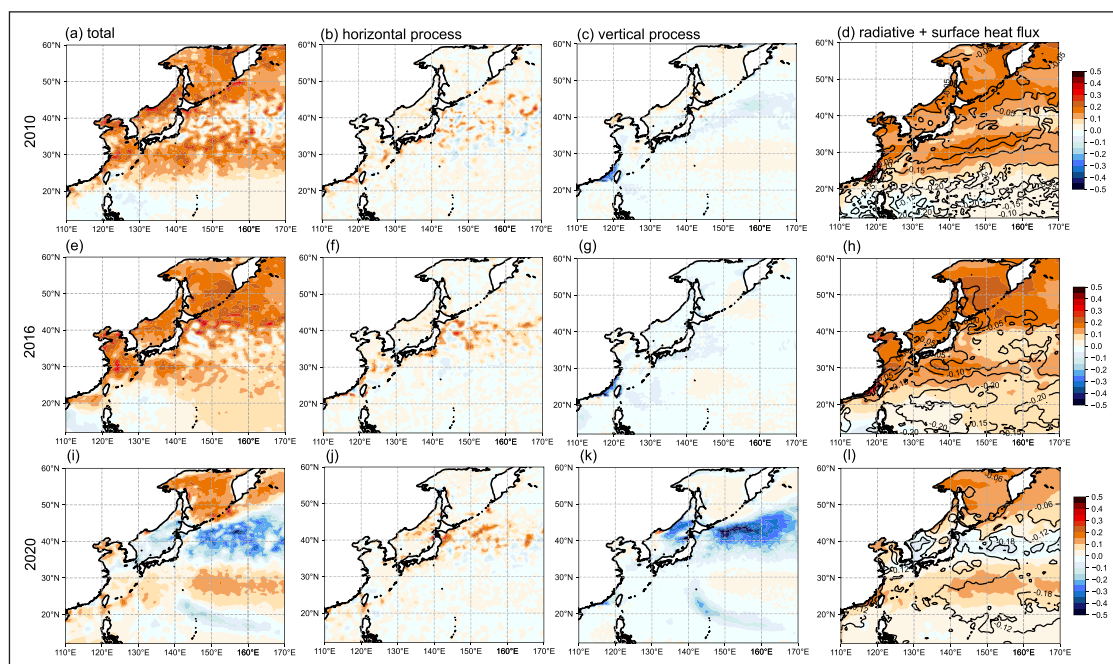


Figure 14 Distributions of ML temperature tendencies ($^{\circ}\text{C day}^{-1}$) averaged during each heavy rainfall event, obtained from the ensemble mean of hindcast with 1–4 day lead time. (a), (e), (i): Total tendency, (b), (f), (j): tendency by horizontal processes, (c), (g), (k): tendency by vertical processes, and (d), (h), (l): tendency by radiative and surface heat fluxes (shading: all fluxes; contour lines: sum of tendencies by outgoing fluxes including longwave radiation, sensible and latent heat fluxes). Each row corresponds to the tendency of each event time-averaged over the term.

positive and almost balanced at areas lower than 20°N and around 40°N, which are located at the outer margins of the Pacific high (fourth column of Figure 14). These regions correspond to the region where vertical mixing is dominant, and the region around 40°N corresponds to the outflow region of IVT (Figure 6). If the SST decrease by the vertical mixing is not factored into the prediction model, the latent heat flux will tend to increase in these regions (Figure 12), and this may weaken the Pacific high leading to incorrect IVT fields.

Consequently, the latent heat flux from the ocean plays an important role in the ocean heat budget within ML, but ocean dynamics were also found to be important. An atmospheric model with a SOM can partially suppress unrealistic latent heat increase using a prescribed MLD, compared to the atmospheric model without the SOM. However, the ocean dynamics are not considered in the SOM, so the SST will remain high and the latent heat flux may be overestimated, especially around the Pacific high. This may lead to a weakened Pacific high and failure to accurately predict heavy rainfall.

5 SUMMARY AND CONCLUSIONS

The merits of ocean prediction with respect to heavy rainfall prediction were examined using hindcast experiments. To confirm the superiority of incorporating ocean prediction, both regional atmospheric and coupled models were used. The 2010, 2016, and 2021 heavy rainfall events that were caused by Baiu and stationary fronts were selected for the hindcast experiments. The experiments using an atmospheric model and a coupled model are referred to as RUN-ATM and RUN-CPL, respectively.

In the comparison of accumulated rainfall, it was found that RUN-ATM underestimated the accumulated rainfall, and the rainfall tended to decrease as the lead time increased. This rainfall decrease was suppressed in RUN-CPL. This feature was found to be independent of atmospheric river (AR) activity. A comparison of the accumulated rainfall distribution suggested that the hindcast cases predicted qualitatively similar rainfall compared with the reanalysis data, but the accumulated amount was dependent on the prediction model, as RUN-ATM underestimated the rainfall especially in the Kyushu area. Forecast skill scores for heavy rainfall prediction indicated that RUN-CPL had higher skill to capture the heavy rainfall occurrence than RUN-ATM, even in a longer lead time.

The cause of underestimated rainfall was analysed through the properties of water vapor. The Integrated Water Vapor (IWV) analysis showed that all cases predicted qualitatively similar patterns compared to the reanalysis data, but some deviations in the low-level wind velocities around Pacific high and IWV in the southwest of Japan were observed depending on the prediction model.

When the lead time increased, the Integrated Vapor Transport (IVT) decreased in the regions southwest and south of Japan, and the decrease was more significant for RUN-ATM than for RUN-CPL. The results suggest that the pressure patterns that dominated the IVT distributions were different for each prediction model, and they were further degraded in RUN-ATM with a same lead time.

The predicted sea level pressure (SLP) patterns were next analysed. When the lead time increased, the SLP decrease at the Pacific high became more significant for RUN-ATM than that for RUN-CPL. However, the SLP at the Pacific high was similar across models for the 2016 event. When the SLP difference between the Pacific high and the area over Japan was analysed, it was found that it became smaller in RUN-ATM compared with the reanalysis data and RUN-CPL for the all events. This suggests that the SLP difference rather than the SLP at the Pacific high is important for prediction performance. The smaller SLP difference indicates that the anticyclonic and cyclonic circulations by the Pacific high and Japan island areas were weak in RUN-ATM, and resulted in weak IVT and underestimated rainfall.

The cause of the incorrect SLP patterns was analysed in terms of the various heat fluxes from the ocean. It was found that the latent heat flux was the most significant among the heat fluxes from the ocean. The latent heat flux was overestimated by RUN-ATM, enhancing convection and weakening the Pacific high. Analysing the relation between SLP and the latent heat flux, it was found that air-sea decoupling enhanced SLP increase in the region southwest of Japan, resulting in a higher SLP over Japan which led to a small SLP difference, especially in 2016 event. Thus, it can be concluded that the entirely incorrect pressure patterns generated by RUN-ATM were derived from the air-sea decoupling (only positive feedback from the sea surface temperature (SST) on the atmosphere) in the atmospheric model.

Finally, the heat budget of the ocean during the heavy rainfall events was analysed. In RUN-CPL, the ocean mixed layer depths (MLDs) in each event were quantitatively well predicted compared with the observed data. The MLD at Pacific high was very thin compared to MLDs in other seasons, and had a large variability; thus, it was found to be difficult to consider the spatial and seasonal variability of MLDs in a slab ocean model. The heat budget analysis of the ocean mixed layer (ML) showed that ML temperature, i.e., SST, was affected not only by heat exchange at the ocean surface, but also by the vertical mixing process, especially around the Pacific high. This suggests that ocean dynamics play an important role in determining the heat balance within the ML and so the SST, and is therefore important for determining the Pacific high pressure pattern. Ocean prediction is therefore preferable to the slab ocean model to achieve accurate heavy summer rainfall prediction associated with the Baiu and stationary fronts.

In the present study, the merits of ocean prediction were examined for the prediction of summer heavy rainfall events where the influence of fronts was dominant. Similar merits were found for atmospheric river (AR)-related events as shown in Baba (2022). The findings of the present and previous studies therefore imply that ocean prediction can improve heavy rainfall prediction, not only for AR-related events, but also for events without AR and tropical cyclones. The results of the present study also indicate the importance of pressure pattern prediction, especially at the Pacific high. Similarly, Wang et al. (2013) noted that the predictability of the western Pacific subtropical high is linked to those of Asian summer monsoon and western north Pacific tropical cyclone activity. Therefore, the fidelity of the Pacific high is considered one of the keys to improving extreme weather prediction in the area around Japan.

Predicting the influence of the Pacific high on heavy rainfall events is not easy for numerical weather prediction models. As the present MLD analysis showed, the MLD is very thin at the Pacific high during summer (the thickness being approximately one-fourth of that in winter), so the atmospheric feedback to the SST becomes significant. When the atmosphere-only model is used to predict the summer heavy rainfall, the influence of thin MLD, i.e., the significant atmospheric feedback on SST is not considered, then it leads to overestimated latent heat flux and resulting incorrect pressure patterns. Therefore it is hard for atmosphere-only model to accurately predict the Pacific high and related weather events. The Japanese weather prediction is currently conducted using the atmosphere-only models, such as global spectral model (GSM) and mesoscale model (MSM) (JMA 2019; Ishida et al. 2022). Unfortunately, such atmosphere-only models are poor at predicting the Pacific high due to the reasons described above. Therefore, in order to further accurately predict the summer heavy rainfall which is influenced by the Pacific high in a longer lead time, coupled model prediction should be introduced in the future operational forecast system.

DATA ACCESSIBILITY STATEMENT

The datasets of hindcast experiments generated during and/or analysed are available from the corresponding author on reasonable request.

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model used in Figures 1 and 2 were originally provided by the Japan Meteorological Business Support Center and downloaded from the Research Institute for Sustainable Humanosphere (RISH) data server of Kyoto University (<http://database.rish.kyoto-u.ac.jp/index-e.html>). ERA5 and ORAS5 were provided by European Centre for Medium-Range Weather Forecasts (ECMWF) via Copernicus Climate Change Service (C3S, <https://climate.copernicus.eu>). OISSTv2 datasets were obtained from National Oceanic and Atmospheric Administration (NOAA) Physical Sciences Laboratory (<https://psl.noaa.gov/data/gridded/data.noaa.oisst.v2.html>). The datasets of Argo was obtained from Argo data products of the international Argo program (<https://argo.ucsd.edu/data/argo-data-products/>).

COMPETING INTERESTS

The author has no competing interests to declare.

AUTHOR CONTRIBUTIONS

Yuya Baba contributed to the conception and design, validation, analysis, investigation, visualization, writing original draft, reviewing, and editing.

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