Observing System Simulation Experiments of a Rich Phased Array Weather Radar Network Covering Kyushu for the July 2020 Heavy Rainfall Event

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Abstract

This study investigates a potential impact of a rich phased array weather radar (PAWR) network covering Kyushu, Japan on numerical weather prediction (NWP) of the historic heavy rainfall event which caused a catastrophic disaster in southern Kumamoto on 4 July 2020. Perfect-model, identical-twin observing system simulation experiments (OSSEs) with 17 PAWRs are performed by the local ensemble transform Kalman filter (LETKF) with a regional NWP model known as the Scalable Computing for Advanced Library and Environment-Regional Model (SCALE-RM) at 1-km resolution. The nature run is generated by running the SCALE-RM initialized by the Japan Meteorological Agency (JMA) mesoscale model (MSM) analysis at 1800 IST 3 July 2020, showing sustained heavy rainfalls in southern Kumamoto on 4 July. Every 30-second synthetic reflectivity and radial winds are generated from the nature run at every model grid point below 20-km elevation within 60-km ranges from the 17 PAWRs. Two different control runs are generated, both failing to predict the heavy rainfalls in southern Kumamoto. In both cases, assimilating the PAWR data improves the heavy rainfall prediction mainly up to 1-hour lead time. The improvement decays gradually and is lost in about 3-hour lead time likely because the large-scale Baiu front dominates.

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1. Introduction

In early summer, a monsoon front called the “Baiu front” yields a rainy season in Japan. The associated southwestern monsoon brings abundant moisture and contributes to activating intense rain systems, which occasionally develop extensively and result in catastrophic disasters (e.g., Nimomiya and Shibagaki 2003; Kato and Goda 2001; Kato 2006; Unuma et al. 2016; Kawano and Kawamura 2020; Tsuji et al. 2020). On 4 July 2020, southern Kumamoto encountered extreme heavy rainfalls associated with the Baiu front. A large amount of moisture continued to flow into southern Kyushu from 3 to 4 July. Many gauge stations of the Japan Meteorological Agency (JMA) observed heavy rainfalls over 400 mm per day on 4 July. This caused catastrophic flooding of River Kuma in southern Kumamoto, with devastating 65 fatalities and 5512 destructions according to the Cabinet Office (2020).

In severe rainfall systems associated with the Baiu front like the case of July 2020, active convection often plays an essential role. Convective clouds rapidly develop within the order of 10 minutes or so, and it is essential to detect early stages of their development for better predictability (e.g., Kawabata et al. 2011). Although several studies investigated the mechanisms and predictability of the July 2020 event, no study focused on individual convection which drastically evolved in several minutes (Fig. 1). Previous studies about this event include Araki et al. (2020) who investigated the importance of the upper cold air for developing deep active convections. Hirokawa et al. (2020) reported the characteristics of the continuously developing quasi-linear rainbands from a statistical point of view. They showed that a linear rainband extended over 270 km for more than 10 hours and repeatedly brought heavy precipitation exceeding 200 mm per 3 hours. Duc et al. (2021) performed an experiment with a 3-hour-update, 1000-member local ensemble transform Kalman filter (LETKF; Hunt et al. 2007; Miyoshi and Yamane 2007) at 5-km resolution and showed that the deterministic and probabilistic forecast skills outperformed those of the operational forecasts by the JMA operational mesoscale model (MSM). Taylor et al. (2021) reported the predictability of this event at relatively low 18-km resolution using the near real-time regional numerical weather prediction (NWP) system known as the SCALE-LETKF (Lien et al. 2017), which consists of the LETKF and a regional NWP model called SCALE-RM standing for the Scalable Computing for Advanced Library and Environment-Regional Model (Nishizawa et al. 2015). The ensemble-mean 5-day rainfall total forecasts by SCALE-LETKF agreed well with the integration of 1-km-mesh JMA precipitation analysis, whereas the heavy rainfall prediction over Kumamoto and Kagoshima prefectures was underestimated. It is still an open question what would be the benefit of capturing rapidly developing convective phenomena to the predictability of a synoptic-scale linear rain band in the July 2020 event. To address this issue, much more rapidly updated and higher-resolution data assimilation experiments should be performed. For this purpose, the phased array weather radar (PAWR; Yoshikawa et al. 2013; Ushio et al. 2015) is capable to capture rapid development of convective clouds every 30 seconds at roughly 100-m three-dimensional spatial resolution without gap. Miyoshi et al. (2016a, 2016b) developed a revolutionary NWP system with a 30-second-update, 100-m-mesh LETKF using a PAWR at Osaka University. Maejima et al. (2017, 2020) showed the impacts of a 30-second update PAWR data assimilation on a prediction for an isolated convective system. These studies used a single PAWR with an observing range of a 60-km radius and focused on convective-scale data assimilation in the limited area. However, no studies have investigated potential benefits of having a network of PAWRs covering a large area for prediction of an extensive convective activity such as the July 2020 rainfall event associated with the Baiu front.

This study aims to investigate a potential impact of a rich
PAWR network covering entire Kyushu on the prediction of the July 2020 heavy rainfall event. Perfect-model, identical-twin observing system simulation experiments (OSSEs) with dense and frequent PAWRs are performed by the SCALE-LETKF system at 1-km resolution and 30-second updates. Section 2 describes the experimental design, and Section 3 presents the results and discussions. Finally, Section 4 provides the concluding remarks.

2. Experimental design

2.1 Nature run and synthetic observation

This study performs perfect-model, identical-twin OSSEs. First, the nature run is generated using the SCALE-RM at 1-km resolution. The same SCALE-RM is used for the OSSEs which will be described in the next subsection. To generate the nature run, the SCALE-RM is initialized by the Japan Meteorological Agency Meso Scale Model (JMA MSM analysis; JMA 2019) at 1800 JST (Japan Standard Time, UTC+9) 3 July 2020 and is run for 16 hours, including the heavy rainfalls in southern Kumamoto from 0400 to 1000 JST, 4 July. Here, the 5-km-mesh JMA MSM data are bilinearly interpolated to the SCALE-RM’s 1-km-mesh grid. The model domain with 660-by-660 horizontal grid points is shown in Fig. 2a or equivalently Fig. 2b innermost domain D3, and the workflow of the nature run is shown in Fig. 2c. Hourly boundary data are taken from the JMA MSM forecast initialized at 1800 JST 3 July. Fifty terrain-following vertical model levels ($z^*$-coordinate levels; e.g., Phillips 1957; Gal-Chen and Sommerville 1975) cover up to 22.5 km high. Sub-grid-scale turbulences are considered by an improved Mellor-Yamada level-2.5 scheme (Nakanishi and Niino 2006). The 6-category single moment bulk microphysics (Tomita 2008) is used for cloud microphysical processes. Model grid point data are output every 30 seconds to generate synthetic PAWR reflectivity and radial winds from 0230 to 0400 JST, 4 July for investigating the short-range predictability of heavy rainfalls from 0400 to 1000 JST (Fig. 2d). The nature run at 1-km resolution represents the intense rain mixing ratio exceeding 5 g kg\(^{-1}\) at 32.25°N shown by the black dashed line in (a) from 0325 JST to 0330 JST. Panels are arranged similarly to Fig. 1 of Miyoshi et al. (2016a) with the real-world PAWR reflectivity data.

Fig. 1. (a) Rain mixing ratio at the 1.5-km level at 0325 JST, 4 July 2020. (b-l) Every-30-second frames of the vertical cross-section of rain mixing ratio [g kg\(^{-1}\)] at 32.25°N shown by the black dashed line in (a) from 0325 JST to 0330 JST. Panels are arranged similarly to Fig. 1 of Miyoshi et al. (2016a) with the real-world PAWR reflectivity data.
real-world PAWR observation. The nature run shows high values of accumulated rainfalls for 12 hours from 2100 JST 3 July to 0900 JST 4 July, similar to the actual JMA gauge station data. For example, 330 mm (nature run)−339.0 mm (JMA gauge) at Hito-yoshi, 191 mm−167.5 mm at Yatsushiro and 392 mm−414.5 mm at Minamata in Kumamoto. Therefore, the nature run at 1-km resolution well captures the intensity of this heavy rainfall event.

In this study, we simulate observations of 17 PAWRs located at local meteorological offices and special automated weather stations in Kyushu (Fig. 2a, red dots). According to the specifications of an actual PAWR at Osaka University (Yoshikawa et al. 2013; Ushio et al. 2015), the synthetic observing range of each PAWR is set to 60 km, and entire Kyushu is covered by the 17 PAWR observation ranges (orange shaded areas in Fig. 2a). To synthesize reflectivity dBZ from the 1-km-resolution nature run, we apply the observation operator of Amemiya et al. (2020) as follows:

\[ Z = (2.53 \times 10^4 \rho_{QR})^{1.84} + (3.48 \times 10^4 \rho_{QS})^{1.66} + (5.54 \times 10^3 \rho_{QG})^{1.70}, \]  
\[ \text{dBZ} = 10 \log_{10}(Z) \]  

where \( \rho \), QR, QS and QG are air density \([\text{kg m}^{-3}]\), mixing ratios of rain, snow and graupel \([\text{g kg}^{-1}]\), respectively. For radial velocity \( V_r \), the observation operator described by Sun and Crook (1997) is used as follows:

\[ V_r = u \cos \alpha \sin \beta + v \cos \alpha \sin \beta + (w - w_t) \sin \alpha, \]  

where \( \alpha, \beta, u, v, w \) and \( w_t \) are the elevation and azimuth angles \([\text{radian}]\), zonal, meridional, and vertical wind components \([\text{m s}^{-1}]\), and reflectivity weighted terminal velocity of droplets \([\text{m s}^{-1}]\) (Lin et al. 1983), respectively. We assume that the PAWR data are available at every model grid point up to 20-km elevation within the observation range shown by orange shades in Fig. 2a. SCALE-RM applies a stretching vertical coordinate using a hyperbolic tangent function so that the minimum grid spacing at the lowest level is 50 m and the averaged grid spacing is 441 m. Since the SCALE-RM has 50 vertical levels with two layers above 20 km, the PAWR data has 48 vertical layers. Following Maejima et al. (2017, 2020), independent white observational noise is added to each datum; the error standard deviations are assumed to be 10% for both reflectivity and radial velocity but floored at 2 dBZ if it becomes less than 2 dBZ for reflectivity. The observation error standard deviation for radial winds is assumed to be 3 m s\(^{-1}\).

2.2 OSSE

This study performs perfect-model, identical-twin OSSEs, in which we use the identical SCALE-RM in the nature run and OSSEs. The initial conditions of the OSSEs are completely blind to the nature run, and the OSSEs receive information of the nature run by assimilating noisy and imperfect observations. We verify the OSSEs by comparing with the nature run. The detailed workflow is illustrated in Fig. 2d. The parent data come from the 6-hourly-update, 18-km-mesh near real-time SCALE-LETKF system of Lien et al. (2017) with 50 ensemble members (Fig. 2d, blue bar), completely independent of the nature run. The model domain is shown by D1 in Fig. 2d, with 320-by-240 grid points.
Conventional observations from the U.S. National Centers for Environmental Prediction (NCEP) known as the NCEP PREPBUFR data are assimilated, including upper-air and surface in-situ observations and satellite-derived data such as satellite winds but excluding radiance data. Lateral boundary conditions are obtained from the NCEP Global Forecasting System (GFS) at 0.5° resolution. For more details of the SCALE-LETKF system for the outermost domain D1, refer to Lien et al. (2017).

Next, downscaled 50-member ensemble simulations with the nested domain D2 with 300-by-300 grid points (Fig. 2b) are performed at 6-km resolution for OSSEs (Fig. 2d, green bars). To create the initial and boundary conditions for the first OSSE (OSSE-1), we perform an ensemble run initialized at 0900 JST 1 July, 3 days before the heavy rainfalls in Kumamoto (Fig. 2d, upper green bar). OSSE-1 at 1-km resolution is initialized at 0100 JST 4 July (Fig. 2d, upper yellow bar). Here, the 1-km-mesh model for the innermost domain D3 (Fig. 2b) is identical to the one used for the nature run. The boundary conditions for the OSSEs are independent of those for the nature run, so that the OSSEs are blind to the nature run except for the observation data (Figs. 2c and 2d). The first 1.5-hour period from 0100 to 0230 JST is considered as a spin-up, and no data are assimilated (Fig. 2d, upper yellow bar). Subsequently, 30-second update data assimilation cycles with every 30-second synthetic PAWR data are performed for the 1.5-hour period from 0230 to 0400 JST (Fig. 2d, upper orange bar). The Gaussian localization functions with the standard deviations of 3 and 1 km are used for the horizontal and vertical covariance localization, respectively. This experiment with PAWR data assimilation is labeled as “30SEC”. For reference, the same procedure as 30SEC but without PAWR data assimilation is performed as the baseline experiment (NO-DA). In addition, the same procedure as 30SEC but with reduced radar data which mimics conventional radars is performed for comparison (5MIN).

To evaluate every 5-minute 1.5-layer PAWR data reduction, similar frequency and vertical density to the conventional radar network, we create a 15-level vertical stretching coordinate based on the 48-level coordinate of the SCALE-RM below 20 km, or the PAWR data for 30SEC. The grid spacings of the 48 levels are simply multiplied by 15/48, so that the minimum grid spacing at the lowest level is 160 m and the averaged grid spacing is 1433 m. Next, the PAWR data for 30SEC is interpolated so that the radar data grid corresponds to the grid sizes of 5MIN. Temporally, every 30-second data is simply thinned to every 5 minutes. Finally, we perform 6-hour forecast experiments initialized by the ensemble-mean states of 30SEC, 5MIN and NO-DA at 0400 JST to investigate the predictability of heavy rainfalls from 0400 to 1000 JST.

The above procedure for OSSE-1 includes information from NCEP PREPBUFR observations only until 0900 JST 1 July, 3 days before the start of OSSE-1 spin-up. This may not be a fair choice for the baseline experiment NO-DA, and the impact of PAWR data assimilation may be overly emphasized. To investigate the sensitivity to the choice of the baseline experiment, the second OSSE (OSSE-2) is performed by taking the information from NCEP PREPBUFR observations until 1500 JST 3 July, about 12 hours before the heavy rains in Kumamoto (Fig. 2d, bottom part). Considering the spin-up for the 6-km-mesh domain D2 experiment, this would be the latest data. This OSSE-2 is identical to OSSE-1 except the initial time for the 6-km-mesh domain D2 experiment.

3. Result

We first focus on OSSE-1. Figure 3 shows the time series of the analysis and forecast root mean square errors (RMSE) for radar reactivity [dBZ] at the 2-km elevation for the 1.5-hour period of LETKF analysis-forecast cycles. The verification area is inside the PAWR observational range (Fig. 2a, orange shaded area). To convert from precipitation mixing ratio in the model to radar reactivity, we use the observation operator described in section 2 (Amemiy et al. 2020). In 30SEC, the RMSE drops rapidly (Fig. 3, blue) in about 10 minutes, i.e., 20 LETKF cycles, and reaches to the asymptotic level of about a quarter of NO-DA (Fig. 3, red). However, in 5MIN, although the RMSE drops gradually before 15 LETKF cycles (0345 JST), it is three times larger than that in 30SEC (Fig. 3, green and blue). Moreover, in the last three LETKF cycles (after 0350 JST), the RMSE seems to be almost constant (Fig. 3, green). Therefore, the RMSE in 5MIN does not seem to reach the similar level as that in 30SEC, mainly because the error grows rapidly in the 5-minute evolution. As shown in Fig. 1, 5-minute-apart radar images have a big discrepancy due to the rapid convective evolution. Therefore, 5-minute-apart data are not frequent enough to capture the evolution and prevent us from taking full advantage of four-dimensional data assimilation of accumulating information in time.

Figure 4 shows the side-by-side comparisons of rain mixing ratio (QR) [g kg$^{-1}$] at the 1.5-km level. The nature run (Fig. 4d) shows that a high QR area corresponding to the heavy rainfalls near the disaster site in southern Kumamoto (Fig. 4d, black circles) stays in a similar location during the period from 0400 to 0800 JST. The maximum QR maintained more than 2 g kg$^{-1}$ near the disaster site. NO-DA at 0400 JST shows high peak values of QR > 2 g kg$^{-1}$, but the location is shifted approximately 80-km southward compared to the nature run (Figs. 4a0 and 4d0). This is associated with a synoptic scale dislocation of the Baiu front. The southward shift persists in the forecast period, and the predicted QR around the disaster site are almost missing (Figs. 4a1−4a4, and 4d1−4d4, black circles). In 5MIN, QR around the disaster site is slightly improved compared with NO-DA in the analysis at 0400 JST (Figs. 4a0 and 4b0, black circles), although it is less than 25% of that in the nature run (Figs. 4b0 and 4d0). After 0500 JST (1-hour forecast), the rain patterns become almost identical to those in NO-DA (Figs. 4a1−4a4, and 4b1−4b4).

By contrast, 30SEC clearly captures the heavy rains in the analysis at 0400 JST (Figs. 4c0 and 4d0). High QR area > 1 g kg$^{-1}$ extends in the west-southwest-east-northeast direction. The peak intensity around the disaster site shows more than 2 g kg$^{-1}$ which agrees well with the nature run (Figs. 4c0 and 4d0). At 0500 JST (1-hour forecast), 30SEC shows high QR > 1 g kg$^{-1}$ close to the nature run. The location of the intense rain area also agrees well with nature run near the disaster site (Figs. 4c1 and 4d1, black circles). However, the western side of this synoptic rainfall system is similar to NO-DA ratios, but the nature run likely because of the limited PAWR range on the western edge over the ocean and the general eastward flow. At 0600 JST (2-hour forecast), the whole rain system generally moves to the east, although high QR > 1 g kg$^{-1}$ is still predicted around the disaster site (Figs. 4c2 and 4d2, black circles). After 0700 JST (3-hour forecast), the overall rain patterns are more similar to NO-DA than the nature run likely because the atmospheric conditions outside the PAWR observation range affected by the boundary data would be more important in this forecast range. The inflow from the western boundary gradually penetrates the computational domain, and the impact of PAWR data assimilation also moves to the east and fades away accordingly. If we look at the downstream regions such as the east of Kyushu, the rain patterns are generally more similar to the nature run than NO-DA even at 0800 JST. This suggests that the PAWR data assimilation in the upstream regions be useful.

To evaluate the forecast accuracy quantitatively, fractions skill scores (FSSs, Roberts and Lean 2008) are shown by the solid lines in Fig. 5. The verification area is the entire model domain at 1-km resolution (Figs. 2a and 2b). FSSs of NO-DA stays less than 0.2 for the entire period from 0400 to 1000 JST (Fig. 5, red solid line). 30SEC (blue solid line) is clearly superior to other cases up to about 0700 JST. Although 5MIN is slightly better than NO-DA at 0400 JST, the advantage is lost by about 0500 JST (red and green solid lines).

As discussed above, OSSE-1’s baseline experiment NO-DA may not be a fair choice, and OSSE-2 is designed to have a better baseline experiment. The only difference between OSSE-1 and OSSE-2 is the choice of the initial conditions. OSSE-2 aims to investigate the impact of PAWR data assimilation in case of the better baseline experiment. As expected, OSSE-2’s NO-DA
generally outperforms OSSE-1’s NO-DA until 0700 JST (Fig. 5, red lines). Although there is a slight improvement in NO-DA until 0700 JST, OSSE-2 leads to generally the same conclusion as OSSE-1. Namely, 30SEC agrees well with the nature run at 0400 JST. A similar figure to Fig. 4 but for OSSE-2 is shown in Fig. S1 in Supplement 1.

The above results demonstrated that dense and frequent PAWR data assimilation improved the heavy rainfall forecast for the first 2- to 3-hour period. Since a typical lifecycle of individual convection is limited to up to an hour, the PAWR data assimilation would have created more suitable environment for continuous convective development. The general eastward flow moved the whole convective systems to the east, but the convective systems did not decay within a single lifecycle of an hour or so. To understand how the convective development is maintained, we investigate equivalent potential temperature (EPT) [K] and horizontal winds near the surface [m s\(^{-1}\)] in OSSE-1 (Fig. 6). The nature run shows clear cold pools in the heavy rain area and a pronounced southwesterly high EPT (> 350 K and > 20 m s\(^{-1}\)) inflow associated with the synoptic-scale Baiu front (Fig. 6d). These are the key features to maintain the heavy rainfalls in the nature run. 30SEC generally agrees in showing clear surface cold pools and the southwesterly
Inflow of high EPT airmass (> 350 K and > 10 m s⁻¹) although slightly dislocated because the southwesterly high EPT airmass inflow is not as prominent (Fig. 6c). Hence, assimilating every-30-second PAWR data contribute to improve the convective development in the severe rainfall area. By contrast, NO-DA shows no surface cold pool or southwesterly high EPT inflow (Fig. 6a) because the main rainband associated with the Baiu front is shifted southward by about 80-km (Fig. 4a) and because moisture supply from the synoptic scale high EPT airmass is limited (Fig. 6a, black ellipse). The magnitude of southwesterly wind is about half level from the synoptic scale high EPT airmass is limited (Fig. 6a, black ellipse) although the synoptic scale high EPT inflow is similar to NO-DA because of the southerly dislocation of the main rainband (Figs. 4a, 4b, 6a, and 6b). Therefore, the intense rainband does not form near the disaster site in 5MIN.

Figures 6e–6h shows the vertical structure of the EPT and upward motion at 32.1°N (Figs. 6e–6h). In the nature run, a rich moist air-mass indicated by the high EPT > 350 K is intensely transported to the upper layers associated with a surface cold pool at 130.7°E (Fig. 6h). In 30SEC, the high EPT (> 350 K) and the intense updraft (> 15 m s⁻¹) are generated above a surface cold pool (Fig. 6g). The high EPT air-mass is accompanied by an intense upward motion which creates more unstable stratification, contributing to the intensification of the convective activities. By contrast, in NO-DA, the relatively dry air-mass indicated by EPT < 344 K flows from the western boundary at the level of 1-km to 3-km (Fig. 6e). In 5MIN, although high EPT airmass and upward motion are found above the surface cold pool, the maximum EPT is lower by 5 K, and the magnitude of upward motion is less than 1/3 compared to 30SEC.

To quantify the time series of the unstable conditions, Fig. 7 shows convective available potential energy (CAPE) [J kg⁻¹] in OSSE-1. At 0400 JST (analysis) the nature run shows unstable areas of large CAPE > 2000 J kg⁻¹ (Fig. 7d, black ellipses), well corresponding to the location of the intense rainband of QR > 1 g kg⁻¹ (Figs. 4d and 7d). 30SEC also shows unstable conditions of relatively large CAPE > 1000 J kg⁻¹ at 0400 JST (Fig. 7c0). The local upward motion with high EPT due to the surface cold pool contributed to generate high CAPE. But after 0500 JST (1-hour forecast), CAPE drops rapidly and becomes similar to NO-DA and 5MIN (Figs. 7a and 7b). As the forecast progresses, the general eastward motion from the southwestern boundary gradually penetrates the computational domain, and the impact of 30-second-update PAWR data assimilation also moves to the east and fades away accordingly. Subsequently, the whole rainfall system consistently flows downstream to the east, and the unstable condition is eliminated. The overall rain pattern of 30SEC is more similar to NO-DA than the nature run after 0700 JST (3-hour forecast), likely because the atmospheric conditions outside the PAWR observation range affected by the boundary data would be more important in this forecast range (Fig. 4).

So far, we discussed the positive impacts of the PAWR data assimilation on the mixing ratio, cold pool and CAPE in the analyses (Figs. 4, 6, and 7). Here, we further discuss why the impacts gradually disappear in the 2- to 3-hour forecast period. Figure 7 (c0)–(c2) shows the positive impact of PAWR data assimilation indicated by large CAPE until 0500 JST, and the CAPE drops by 0600 JST. The gradual decay in the 2- or 3-hour forecast period would be probably because the convection improved by assimilating the PAWR data could improve the prediction of the immediate successor. Namely, the large CAPE at 0500 JST would likely contribute to develop a new convection as the immediate successor, which causes rainfalls after 0500 JST. It is natural that such a succession effect would not continue for multiple times due to the chaotic nature of convective phenomena. In the OSSE-1, 2- or 3-hour precipitation forecast may be a limit of the positive impact of the PAWR data assimilation. The above discussions also apply to OSSE-2. The similar figures to Figs. 6 and 7 but for OSSE-2 are shown in Figs. S2 and S3 in Supplement 1.
4. Conclusion

This study performed 1-km-mesh, 30-second update OSSEs by the SCALE-LETKF (Lien et al. 2017) to investigate the potential impact of a rich PAWR network covering entire Kyushu on NWP of the heavy rainfall event on 4 July 2020. The 1-km-mesh nature run was generated by the SCALE-RM (Nishizawa et al. 2015), and every 30-second PAWR reflectivity and radial wind were synthesized from the nature run. NO-DA failed to predict the heavy rain because of the synoptic dislocation of the Baiu front. By contrast, 30SEC assimilating the PAWR data showed the rain area similar to the nature run, and predicted the heavy rainfall in Kumamoto, mainly for the first hour. However, 5MIN showed almost no improvement, where the PAWR data were reduced in time and space to mimic similar observing frequency and density of conventional radars. FSSs indicated that 30SEC was superior to 5MIN and NO-DA. These results suggest potential advantage of the dense and frequent PAWR data assimilation in the July 2020 event. The FSS of an additional OSSE-2 with a better NO-DA showed basically the same conclusion. Longer data assimilation cycles might contribute to more improvement, but the sensitivity to the cycling period remains to be a subject of future research.

Although the previous PAWR data assimilation studies focused on using a single PAWR (Miyoshi et al. 2016a, 2016b; Maejima et al. 2017, 2019, 2020; Lien et al. 2017), this study showed a promise of using a rich PAWR network covering a large area for organized convective systems. However, this study assumed unrealistic idealized assumptions as the first step, such as the perfect model, an ideal fusion of multiple radar data, and no quality issue of the PAWR data. Further investigations with more realistic assumptions are needed to refine the results. We hope that this first step would create a path toward large-scale installation of powerful PAWRs to reduce the human damages associated with heavy rainfall under the changing climate.

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Supplement

Supplement 1 provides the results of OSSE-2.

References

Amemiya, A., T. Honda, and T. Miyoshi, 2020: Improving the observation operator for the phased array weather radar in the SCALE-LETKF system. SOLA, 16, 6–11.

Araki, K., T. Kato, Y. Hirockawa, and W. Mashiko, 2020: Characteristics of atmospheric environments of quasi-stationary convective bands in Kyushu, Japan during the July 2020 heavy rainfall event. SOLA, 17, 8–15. doi:10.2151/sola.2021-002.

Duc, L., T. Kawabata, K. Saito, and T. Oizumi, 2021: Forecasts of the July 2020 Kyushu heavy rain using a 1000-member ensemble Kalman filter. SOLA, 17, 41–47.

Hirockawa, Y., T. Kato, K. Araki, and W. Mashiko, 2020: Characteristics of an extreme rainfall event in Kyushu district, southwestern Japan in early July 2020. SOLA, 16, 265–270.

Hunt, B. R., E. J. Kostelich, and I. Szunyogh, 2007: Efficient data assimilation for spatiotemporal chaos: A local ensemble transform Kalman filter. Physica D, 230, 112–126.

Gal-Chen, T., and R. Sommerville, 1975: On the use of a coordinate system having some special advantages for numerical forecasting. J. Comput. Phys., 17, 209–228.

Government of Japan, 2020: Reports on the heavy rain event of July 2020 (Available online at: http://www.bousai.go.jp/updates/r2070oame/pdf/r20703_oame_36.pdf, accessed 20 March 2021) (in Japanese).

JMA, 2019: Appendix to WMO Technical Progress Report on the Global Data-processing and Forecasting System and Numerical Weather Prediction Research. Outline of the operational numerical weather prediction at the Japan Meteorological Agency. Japan Meteorological Agency, Tokyo, Japan. 188 pp. (Available online at https://www.jma.go.jp/jma-eng/jma-center/nwp/outline2019-nwp/index.htm, accessed 20 March 2021)

Kato, T., 2006: Structure of the band-shaped precipitation system inducing the heavy rainfall observed over northern Kyushu, Japan on 29 June 1999. J. Meteor. Soc. Japan, 84, 129–153.

Kato, T., and H. Goda, 2001: Formation maintenance processes of a stationary and band-shaped heavy rainfall observed in Niigata on 4 August 1998. J. Meteor. Soc. Japan, 79, 899–924.

Kawabata, T., T. Kuroda, H. Seko, and K. Saito, 2011: A cloud-resolving 4D-Var assimilation experiment for a local heavy rainfall event in the Tokyo metropolitan area. Mon. Wea. Rev., 139, 1911–1931.

Kawano, T., and R. Kawamura, 2020: Genesis and maintenance processes of a quasi-stationary convective band that produced record-breaking precipitation in Northern Kyushu, Japan on 5 July 2017. J. Meteor. Soc. Japan, 95, 673–690.

Lien, G.-Y., T. Miyoshi, S. Nishizawa, R. Yoshida, H. Hishiro, S. A. Adachi, T. Yamaura, and H. Tomita, 2017: The near-real-time SCALE-LETKF system: A case of the September 2015 Kanto-Tohoku Heavy Rainfall. SOLA, 13, 1–6.

Lin, Y.-L., R. D. Farley, and H. D. Orville, 1983: Bulk parameterization of the snow field in a cloud model. J. Climate Appl. Meteor., 22, 1065–1092.

Maejima, Y., and T. Miyoshi, 2020: Impact of the window length of four-dimensional local ensemble transform Kalman filter: A case of convective rain event. SOLA, 16, 37–42.

Maejima, Y., M. Kunii, and T. Miyoshi, 2017: 30-second-update 100-m-mesh data assimilation experiments: A sudden local rain case in Kobe on September 11, 2014. SOLA, 13, 174–180.

Maejima, Y., T. Miyoshi, M. Kunii, H. Seko, and K. Sato, 2019: Impact of dense and frequent surface observations on 1-minute-update severe rainstorm prediction: A simulation study. J. Meteor. Soc. Japan, 97, 253–273.

Miyoshi, T., and co-authors, 2016a: “Big Data Assimilation” revolutionizing severe weather prediction. Bull. Amer. Meteor. Soc., 97, 1347–1354.

Miyoshi, T., and co-authors, 2016b: “Big Data Assimilation” toward post-peta-scale severe weather prediction: An overview and progress. P. IEEE, 104, 2155–2179.

Miyoshi, T., and S. Yamane, 2007: Local ensemble transform Kalman filtering with an AGCM at a T519/L48 resolution. Mon. Wea. Rev., 135, 3841–3861.

Nakanishi, M., and H. Niino, 2006: Development of an improved turbulence closure model for the atmospheric boundary layer. J. Meteor. Soc. Japan, 87, 895–912.

National Centers for Environmental Prediction/National Weather Service/NOAA/U.S. Department of Commerce, 2015: NCEP GDAS/FNL 0.25° Global Tropospheric Analyses and Forecast Grids. Research Data Archive at the National Center for Atmospheric Research, Computational and Information Systems Laboratory, updated monthly (Available online at: https://doi.org/10.5065/D65Q4TZ2, accessed 24 April 2021).

Nomomiya, K., and Y. Shibagaki, 2003: Cloud system families in the Minyu-Baiu front observed during 1–10 July 1991. J. Meteor. Soc. Japan, 81, 193–209.

Nishizawa, S., H. Yashiro, Y. Sato, Y. Miyamoto, and H. Tomita, 2015: Influence of grid aspect ratio on planetary boundary layer turbulence in large-eddy simulations. Geosci. Model Dev., 8, 3393–3419.

Phillips, N. A., 1957: A coordinate system having some special advantages for numerical forecasting. J. Atmos. Sci., 14, 184–185.

Robarts, N. M., and H. W. Lean, 2008: Scale-selective verification of rainfall accumulations from high-resolution forecasts of convective events. Mon. Wea. Rev., 136, 78–97.

Saito, K., T. Fujita, Y. Yamada, J. Ishida, Y. Kumagai, K. Aranami, S. Ohtori, R. Nagasawa, S. Kumagai, C. Murao, T. Kato, H. Eito, and Y. Yamazaki, 2006: The operational JMA nonhydrostatic mesoscale model. Mon. Wea. Rev., 134, 1266–1298.

Saito, K., J. Ishida, K. Aranami, T. Hara, T. Segawa, M. Narita, and Y. Honda, 2007: Nonhydrostatic atmospheric models and operational development at JMA. J. Meteor. Soc. Japan, 85B, 271–304.

Sun, J., and A. Crook, 1997: Dynamical and microphysical retrieval from Doppler radar observations using a cloud model and its adjoint. Part I: Model development and simulated data experiments. J. Atmos. Sci., 54, 1642–1661.

Taylor, J., A. Amemiya, T. Honda, Y. Maejima, and T. Miyoshi, 2021: Predictability of the July 2020 heavy rainfall with the SCALE-LETKF. SOLA, 17, 48–56.

Tomita, H., 2008: New microphysical schemes with five and six categories by diagnostic generation of cloud ice. J. Meteor. Soc. Japan, 86A, 121–141.

Tsujii, H., C. Yokoyama, and Y. Takayabu. 2020: Contrasting features of the July 2018 heavy rainfall event and the 2017 Northern Kyushu rainfall event in Japan. J. Meteor. Soc. Japan, 98, 859–876.

Unuma, T., and T. Takemi, 2016: Characteristics and environmental conditions of quasi-stationary convective clusters during the warm season in Japan. Quart. J. Roy. Meteor. Soc., 142, 1232–1249.

Ushio, T., T. Wu, and S. Yoshida, 2015: Review of recent progress in lightning and thunderstorm detection techniques in Asia. Atmos. Res., 154, 89–102.

Yoshikawa, E., T. Ushio, Z. Kawasaki, S. Yoshida, T. Morimoto, F. Mizutani, and W. Wada, 2013: MMSE beam forming on fast-scanning phased array weather radar. IEEE Trans. Geosci. Remote Sens., 51, 3077–3088.

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