Improving the regional model forecasting of persistent severe rainfall over the Yangtze River Valley using the spectral nudging and update cycle methods: a case study

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Abstract

China’s worst flooding since 1998 occurred over the Yangtze River Valley from 30 June to 6 July 2016. This study investigated the event using a new method – the spectral nudging and update cycle (SN+UIC) – in the regional Weather Research and Forecasting model, fuller use of small-scale features by using multi-scale blending. The SN+UIC was found to be successful in improving the prediction of this persistent severe rainfall event; and the larger the magnitude and longer the lead time, the more obvious the improvement. It was also found that the use of this new method decreased the root-mean-square error for related meteorological variables.

Keywords: persistent severe rainfall; precipitation forecasting; spectral nudging; update cycle

1. Introduction

Persistent severe rainfall (PSR) and floods across the southern half of China besieged cities and towns during 0000 UTC 30 June to 0000 UTC 6 July 2016. In fact, this was China’s worst flooding event since 1998. The rain band’s range of accumulated rainfall above 250 mm reached 180 000 km², and accumulated precipitation in Wuhan was 520.1 mm. More than 100 people died through drowning or landslides as buildings collapsed. This event can be mentioned in the same breath as the exceptionally serious events in the summer of 1998, as the flooding for both was caused by PSR linked to a strong El Niño weather pattern (Huang et al., 1998; Wang et al., 2015; Shankman and Keim, 2016).

PSR, different from ‘normal’ torrential rain events in that their severe impacts occur over larger areas and longer durations, has been occurring with increased frequency and relatively higher mean intensity in China during the last 60 years (Chen and Zhai, 2013). The abnormally stationary development of the associated large-scale circulation can influence the weather regime transitions and synoptic-scale forecasting setting within which high-impact weather events evolve (Samel and Liang, 2003; Wang et al., 2009; Zhai et al., 2013; Chen and Zhai, 2016).

Global models have an advantage in predicting large-scale atmospheric variation, and regional models are superior in terms of small-scale changes prediction (Chen et al., 2010; Wang et al., 2012; Grazzini and Vitart, 2015; Ma et al., 2015). For the large-scale circulation, spectral nudging (SN) – a scale-selective interior constraint technique (Storch et al., 2000; Miguez-Macho et al., 2004) – in the Weather Research and Forecasting (WRF) model has been widely used, and its application significantly improves the prediction of atmospheric circulation and precipitation forecasts (Zhao et al., 2016). For small-scale changes, blending technique is an effective method to make efficient use of large-scale forecasts of the forcing fields, retain the small-scale features of regional model (Yang, 2005). Some previous studies revealed that the application of blending increases precipitation prediction skills (Wang et al., 2014a, 2014b; Hsiao et al., 2015), however, these studies improved initial conditions (ICs) through assimilation and directed against the regional ensemble prediction within 3 days.
Models with higher spatial resolution perform better when the precipitation is intense (Iorio et al., 2004; Givati et al., 2012; Jang and Hong, 2014; Sikder and Hossain, 2016), while global model-based precipitation forecasts are constrained by computational limitations. In the work reported in this article, we used SN to constrain the interior of the regional model towards the large-scale driving data, along with the ‘update cycle’ method to retain the small-scale features for ICs, by using multi-scale blending (MSB) (Wang et al., 2014a) for 15-day forecasts in WRF, so as to improve the numerical prediction of the PSR event in July 2016 over the Yangtze River Valley. The ultimate goal is to extend the forecast lead time for PSR events and further enhance disaster prevention and mitigation capabilities.

2. Data and methodology

The regional model used was the Advanced Research WRF model (version 3.7.1). The data used to provide the regional model ICs, boundary conditions, and nudging fields were 0.5° × 0.5° Global Forecast System (GFS) data. The initial forecast time was at 0000 UTC for 15-day forecasts in the period 21–29 June 2016. The temporal resolution of the first 10 days of GFS forecasting was 3 h, and for the last 5 days it was 12 h.

WRF was run with a 63-layer configuration that extended to a model top at 10 hPa. Double-deck nesting was used, as shown in Figure 1, with horizontal grid spacings of 12 km (560 × 420 grids) and 4 km (586 × 745 grids). The physical configurations in WRF were kept the same for all experiments; namely, the Kain–Fritsch cumulus convection parameterization scheme (Kain, 2004), the Rapid Radiative Transfer Model longwave radiation scheme (Mlawer et al., 1997), the WRF Double Moment 6-class microphysics scheme (Lim and Hong, 2010), the Dudhia shortwave radiation scheme (Dudhia, 1989), the Yonsei University boundary layer scheme (Hong et al., 2006), the Monin–Obukhov surface layer scheme (Beljaars, 1994), and the Noah land surface scheme (Tewari et al., 2004). The Kain–Fritsch cumulus convection parameterization scheme was just turned on for the 12 km resolution runs. The SN was applied directly on the horizontal wind components, potential temperature, and geopotential height above the planetary boundary layer, with an interval of 6 h. The error growth of a regional model is mainly caused by long waves with scale >2000 km (Vukicevic and Errico, 1990), and large-scale features of >2000 km were nudged for the large domain, as in Liu et al. (2012); the sizes of domains 1 and 2 in this study were about 6720 × 5040 and 2344 × 2980 km (zonal × meridional direction), with the nudging wavenumbers of 4 and 2 for the large and small domains, respectively, and the wavenumbers for the zonal and meridional directions were the same.

The update cycle for the ICs (UIC) was conducted for every 72-h forecast with a 12-h running-in period based on the SN experiments, as shown in Figure 2, four UICs were done by using the MSB (Wang et al., 2014a) to combine the large scales from the GFS with the small scales from the WRF model. As far as (e.g.) the 15-day forecasts were concerned, it was been conducted by five 3-day forecasts. The cut-off wavenumber was chosen to be the same as the threshold wavelength of SN in domain 1, and this method is referred to as SN + UIC. For the MSB, the Two-Dimensional Discrete Cosine Transform method (Denis et al., 2002) was used to filter wavenumber-4 for all variables that SN applied and the water vapour mixing ratio at 62 layers (except the first ground layer).

There were three sets of experiments in this study: SN, SN + UIC, and CTL (control experiments without SN and UIC). The initial forecast times were 1, 3, 5, 7, and 9 days prior to the PSR, as shown in Figure 2. In addition, ‘lead time’ denotes the forecast-start-time (number of days) prior to the PSR event.

In order to objectively validate the new methodology, National Centers for Environmental Prediction/National Centre for Atmospheric Research (NCEP/NCAR) FNL (final) Operational Global Analysis data (Kalnay et al., 1996) were used (horizontal resolution: 1° × 1°; temporal resolution: 6 h), and the root-mean-square error (RMSE) was applied for verification of the geopotential height, temperature, relative humidity, and wind fields. The Threat Score (TS) was used for 24-hour precipitation verification in different precipitation rate categories [light rain (<10 mm day⁻¹), moderate rain (10–24.9 mm day⁻¹), heavy rain (25–49.9 mm day⁻¹), torrential rain (50–100 mm day⁻¹), and rainstorm (>100 mm day⁻¹)], by using the precipitation dataset of basic daily meteorological variables from Chinese national surface weather stations. The whole precipitation process score was obtained by averaging the daily scores of the PSR case period. For the accumulated precipitation, the Brier Score (BS) was used in four rainfall categories [more than 10 mm (>10 mm), 25 mm (>25 mm), 50 mm (>50 mm), and 100 mm (>100 mm)]. The TS
Figure 2. Diagram of the SN + UIC forecast flow with the update cycle covered.

Figure 3. Total accumulative rainfall distribution of PSR for the observation (e), and in the forecast experiments at different lead times [(a1–a4) 1 day; (b1–b4) 3 days; (c1–c4) 5 days; (d1–d4) 7 days] and using the different experiment schemes [(a1–d1) CTL; (a1–d2) SN; (a3–d3) SN + UIC]. Panels a4–d4 are the NCEP GFS forecasts.
and BS can be expressed as

$$\text{TS} = \frac{\text{Hit rate}}{\text{Hit rate} + \text{False rate} + \text{Miss rate}} \quad (1)$$

$$\text{BS} = \frac{1}{N} \sum_{k} (P_k - O_k)^2 \quad (2)$$

$P_k$ and $O_k$ denote the $k$-component probability value of the forecast and observation. BS ranges from zero (0) to one (1) with BS = 0 is a perfect forecast.

The improvement rate (IR) of the BS and RMSE was also calculated, as follows (with BS as the example):

$$\text{IR} = -\frac{\text{BS}_{\text{new}} - \text{BS}_{\text{old}}}{\text{BS}_{\text{old}}} \times 100\% \quad (3)$$

3. Results

The focus of this study was on forecasting the PSR event. We first evaluated the 6-day total precipitation in the WRF simulation with different methods and lead times (Figure 3), which were also compared with the GFS forecast. For the rain band’s range and accumulated rainfall above 100 mm, using the SN + UIC was relatively better when forecasting with a lead time of 5 and 7 days (Figures 3(c1)–(d1)) in the regional model; the rain band’s range of the accumulated rainfall from 50 to 100 mm in GFS was wider than that in the WRF outcomes or observation. For the accumulated rainfall above 200 mm, the SN + UIC (Figures 3(a3)–(b3)) also showed better performance, compared with the SN, for 1- and 3-day lead times (Figures 3(a2)–(b2)), and compared with CTL for the 1-day lead time only (Figure 3(a1)). The coarser GFS forecast did not do well for the accumulated rainfall above 100 mm, especially for 3-, 5-, and 7-day lead times (Figures 3(b1)–(d1)), which can be attributed to the coarse resolution preventing small-scale features from being resolved well (e.g. Kumar et al., 2016). In general, the better performance of the SN + UIC is based on the better ICs, which, via combining the respective advantages of the GFS and WRF forecasts, improves the ICs, and in turn the rain band’s range and accumulated rainfall (especially heavy rainfall) forecasts.

The averaged TSs shown in Figure 4 were used to objectively reveal the ability of the SN + UIC. The...
improvement through using the SN + UIC, compared to the CTL and SN, was mainly reflected in the precipitation rate categories above light rain (>10 mm day⁻¹), i.e. in general, the larger the magnitude, the more significant the improvement (Figure 4(a)). For the different forecast lead times, the improvement of the SN + UIC became increasingly obvious as the lead times increased, and also showed higher TSs for light rain than other methods at 5- and 7-day lead times.

Figure 5 compares the averaged RMSE profiles in the PSR period for the different methods. For the geopotential height field (Figure 5(a)), the SN + UIC and SN led to improvements below 400 hPa, and the SN + UIC was better than the other two methods below 500 hPa and above 400 hPa, where the RMSE was relatively larger. For the temperature and relative humidity (Figures 5(b) and (c)), the SN + UIC was better than the SN; plus, it performed better than the CTL below 400 hPa. In terms of the RMSE of the zonal wind field (Figure 5(d)), the SN + UIC achieved slightly better results than the SN and CTL below 600 hPa, where the RMSE was also relatively larger than at other altitudes. There was a slight degradation for the meridional wind field using the SN and SN + UIC (Figure 5(e)), and further research is needed to explore this issue.

**Figure 5.** Averaged RMSE changes with height in the PSR period with the different schemes: (a) geopotential height field (HGT; units: gpm); (b) temperature field (TC; units: °C); (c) relative humidity (RH; units: %); (d) zonal wind field (U; units: m s⁻¹); (e) meridional wind field (V; units: m s⁻¹).

**Table 1.** The IRs of the averaged BS and RMSE over the different forecast lead times for the PSR period (units: %).

| Meteorological variable | Verification method | SN + UIC versus CTL (%) | SN + UIC versus SN (%) |
|------------------------|---------------------|------------------------|------------------------|
| Accumulated precipitation |
| >100.0 mm BS | -5.9 | -10.7 |
| >25.0 mm | 6.1 | 3.9 |
| >50.0 mm | 6.2 | 16.7 |
| >100.0 mm | 12.1 | 17.9 |
| HGT | RMSE | 7.7 | 46 |
| TC | 3.6 | 4.1 |
| RH | 1.45 | 1.7 |
| U | 1.4 | 1.65 |
| V | -4.7 | -1.3 |

The bold entries mean the positive value.

The IRs of BS and RMSE were calculated (Table 1). For the accumulated precipitation BS, the SN + UIC produced better results for the rainfall above 25, 50, and 100 mm; moreover, the larger the magnitude, the larger the decrease in BS. The average altitude IRs were also shown to be positive for the geopotential height (HGT), temperature, relative humidity, and zonal wind field, compared to the CTL and SN.
Given the uncertain state of atmospheric flow, the ability to forecast fine-scale weather systems decreases with increasing lead time (Lorenz, 1969), so the improvement in the prediction of the accumulated rainfall and related meteorological variables may be due to two important attributes of the new method: (1) making efficient use of large-scale forecasts of the forcing fields by using SN in the WRF for the medium-range forecast, and (2) retaining the small-scale features for ICs with MSB.

4. Summary

A new method for improving the numerical prediction of rainfall was applied to a recent (July 2016) PSR event over the Yangtze River Valley, and its performance explored. Using the WRF model, the results of three experiments using the SN and UIC were analysed and verified, in terms of accumulated rainfall and related meteorological variables.

The results showed that the use of the SN + UIC improved the prediction of the rain band’s range (above 100 mm) at lead times of 5 and 7 days, and the accumulated rainfall above 200 mm at lead times of 1 and 3 days. The larger the magnitude and the longer the lead time, the more obvious the improvement owing to the SN + UIC. In addition, the SN + UIC decreased the RMSE for geopotential height, relative humidity, and temperature below 400 hPa in the PSR period, and below 600 hPa for the zonal wind, with relatively larger RMSE than at other altitudes.

The findings of this study indicate that using the SN + UIC can improve the numerical prediction of events like that of the PSR in July 2016 over the Yangtze River Valley. However, long-term statistical studies, with more cases and a wider range of PSR events in different areas of China, are needed to fully assess the advantages of the SN + UIC and further extend the forecast lead time for PSR events. Such works also should involve some relevant analyses for a better selection of SN + UIC parameters and a deeper understanding of the function of the method.

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