Case Dependence of Multiscale Interactions between Multisource Perturbations for Convection-Permitting Ensemble Forecasting during SCMREX

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ABSTRACT: This study examines the case dependence of the multiscale characteristics of initial condition (IC) and model physics (MO) perturbations and their interactions in a convection-permitting ensemble prediction system (CPEPS), focusing on the 12-h forecasts of precipitation perturbation energy. The case dependence of forecast performances of various ensemble configurations is also examined to gain guidance for CPEPS design. Heavy-rainfall cases over Southern China during the Southern China Monsoon Rainfall Experiment (SCMREX) in May 2014 were discriminated between the strongly and weakly forced events in terms of synoptic-scale forcing, each of which included 10 cases. In the cases with weaker forcing, MO perturbations showed larger influences while the enhancements of convective activities relative to the control member due to IC perturbations were less evident, leading to smaller dispersion reduction due to adding MO perturbations to IC perturbations. Such dispersion reduction was more sensitive to IC and MO perturbation methods in the weakly and strongly forced cases, respectively. The dispersion reduction improved the probabilistic forecasts of precipitation, with more evident improvements in the cases with weaker forcing. To improve the benefits of dispersion reduction in forecasts, it is instructive to elaborate consider the case dependence of dispersion reduction, especially the various sensitivities of dispersion reduction to different-source perturbation methods in various cases, in CPEPS design.

KEYWORDS: Ensembles; Probabilistic Quantitative Precipitation Forecasting

1. Introduction

For regional numerical weather prediction (NWP) models, forecast uncertainties are caused by inaccurate initial (ICs) and lateral boundary (LBCs) conditions and imperfect forecast models, especially model physics (MO). Due to high nonlinearity and rapid error growth at convective scales (Lorenz 1969; Hohenegger and Schär 2007), especially in areas of moist convection (Zhang et al. 2003), it is particularly necessary to explicitly quantify the forecast uncertainties of convection-permitting NWP models (Schwartz 2019). To achieve this goal, convection-permitting ensemble prediction systems (CPEPSs) have been developed since 2007 (Xue et al. 2007), with some NWP centers having established operational or semioperational CPEPSs (Peralta et al. 2012; Bouttier et al. 2012; Hagelin et al. 2017; Clark et al. 2018; Schwartz et al. 2019). Recently, some novel perturbation methods have been proposed to improve CPEPS design by improving the representation of IC (Johnson and Wang 2016; Raynaud and Bouttier 2016) or MO (Wang et al. 2019) uncertainties. Nevertheless, how to optimally design CPEPSs in Southern China remains understudied (Zhang 2018; Luo et al. 2020).

Because ensemble forecasting aims to estimate forecast uncertainties or errors (Leith 1974; Toth and Kalnay 1997), successful ensemble forecasts require all the remarkable sources of forecast uncertainties or errors, i.e., ICs, MO, and LBCs, to be sampled in CPEPS design (Xue et al. 2007; Gebhardt et al. 2011; Vié et al. 2011; Romine et al. 2014). Thus, ensemble perturbations should properly sample the error growth from ICs, MO, and LBCs. To achieve this goal, it is vital to understand the multiscale characteristics of perturbations from different sources and their interactions in CPEPSs (Johnson et al. 2014; Zhang 2019, hereafter Z19).

Some recent studies have shown that the impacts of different-source perturbations on precipitation forecasts of CPEPSs differ in both temporal and spatial scales. The evolution of precipitation forecast perturbations has been illustrated to be influenced more by IC perturbations during the first 12 h than by MO or LBC perturbations in some studies focused on Europe (Hohenegger et al. 2008; Vié et al. 2011; Peralta et al. 2012; Kühneil et al. 2014). However, in the study of Johnson et al. (2011) focused on the Great Plains of the United States, MO perturbations were revealed to have a larger impact than both IC and LBC perturbations for 12-h precipitation forecasts. Johnson et al. (2014) found that large-scale (i.e., on the order of hundreds to thousands of kilometers) IC/MO perturbations are generally more important than small-scale (i.e., on the order of tens of kilometers) IC perturbations in forecasts of precipitation at the scales of 64–4096 km in the United States. Based on the study of Z19 focused on Southern China, the meso-β-scale (20–200 km) MO perturbations for precipitation are found to show faster growth and saturation and larger magnitude than the meso-α-scale (200–1300 km) ones.

For the interactions among IC, MO, and LBC perturbations in CPEPSs, most studies focused on short-term (0–12 h) forecasts have shown that forecast perturbations based on the combination of perturbed IC, MO, and LBCs are larger than

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those generated by perturbing only one or two sources (Peralta et al. 2012; Romine et al. 2014; Surcel et al. 2017). However, adding MO perturbations to IC/LBC perturbations has been found to decrease forecast perturbations for precipitation in some recent studies (Bouttier et al. 2012; Baker et al. 2014; Z19). Such “negative” impacts of adding MO perturbations on ensemble dispersions reflect some effects of perturbed MO configurations in decreasing the amount or position spreading of precipitation and were defined as the “dispersion reduction” in Zhang (2020, manuscript submitted to Quart. J. Roy. Meteor. Soc., hereafter Z20).

In fact, the interactions between IC and MO perturbations in CPEPSs differ at different scales. Based on two case studies, Johnson et al. (2014) found that the enhancement in precipitation perturbation energy (i.e., dispersion enhancement) due to adding MO perturbations to IC perturbations occurs mainly at the scales of 64–512 km. However, the interactions between IC and MO perturbations were not systematically studied in Johnson et al. (2014) due to limited samples. Z19 found that the dispersion reduction due to adding MO perturbations to IC perturbations occurs mainly at the scales of 20–200 km, which partially overlap the scales found by Johnson et al. (2014) to be characterized by dispersion enhancement.

The dispersion reduction was speculated by Bouttier et al. (2012) to be related to the drying effect of MO perturbations. To be specific, the stochastically perturbed parameterization tendency (SPPT) was supposed by Bouttier et al. (2012) to disturb the vertical structure of humidity in precipitating columns, which causes more evaporation of precipitation in the planetary boundary layer (PBL). Complementary to Bouttier et al. (2012) and Z19 interpreted the dispersion reduction based on the different multiscale characteristics between IC and MO perturbations. Specifically, the meso-β-scale dispersion reduction occurs when MO perturbations grow rapidly to their saturation values, which are evidently smaller than the magnitude of forecast perturbations generated by the same IC perturbations applied with the unperturbed model configuration. In the interactions between IC and MO perturbations, the meso-α-scale forecast perturbations are influenced by the upscale growth of saturated meso-β-scale perturbations. The meso-α-scale dispersion reduction occurs responding to the meso-β-scale dispersion reduction, since the faster saturation of forecast perturbations at meso-β scales leads to the faster perturbation saturation at meso-α scales. However, these interpretations of dispersion reduction should be recognized to be still speculative, because calculating precipitation forecast perturbations at gridpoint scales as in Z19 may be unsuited in CPEPSs due to the double-penalty issue (Dey et al. 2016; Weyn and Durrant 2019). The double-penalty issue is more evident at smaller scales and thus may explain the greater dispersion reduction at meso-β than meso-α scales. Consequently, the dispersion reduction needs further investigations with neighborhood-based approaches (Dey et al. 2014, 2016; Johnson and Wang 2016; Flack et al. 2018; Weyn and Durrant 2019). Thus, the multiscale interactions between IC and MO perturbations in CPEPSs are complex and still unclear.

The case dependence of the impacts of different-source perturbations in CPEPSs has been reported in some works. Vié et al. (2011) found that IC perturbations based on perturbed observations exhibit smaller (larger) impacts on forecasts of Mediterranean heavy precipitation in autumn when the synoptic-scale forcing is strong (weak) compared with LBC perturbations. Conversely, both the downscaled LBC and IC perturbations were demonstrated to have similar impacts in the central European warm season with different forcing regimes (Keil et al. 2014; Kühneleit et al. 2014). In Keil and Craig (2011) and Keil et al. (2014), MO perturbations based on perturbed parameters were found to be more important for precipitation forecasting in weak- than strong-forcing regimes in Germany. However, Surcel et al. (2017) found no significant statistical relationship between the effects of MO perturbations based on mixed physics and precipitation coverage or convective equilibrium in the contiguous United States. Despite these studies, it remains inconclusive how different forcing regimes respond to different-source perturbations in CPEPSs, probably due to the differences in the perturbation methods, regions, seasons, and analysis methods among these studies. Thus, it is unknown if the results of these studies are characteristic of cases in other regions with different background flows. Further investigations are necessary to fully understand the case dependence of the impacts of different-source perturbations, which is important for advancing CPEPS designs.

Recently, the case dependence of the multiscale characteristics of multisource perturbations and their interactions in CPEPSs has been investigated. Based on a synoptically forced case and a case characterized by upscale-growth convection, Johnson et al. (2014) concluded that small-scale IC perturbations show more impacts in the latter case and that the impacts of adding MO perturbations to IC perturbations are more evident at larger scales and later lead times in the former case. For convective events in the United Kingdom, Flack et al. (2018) found that forecast perturbations for synoptic-scale-forcing cases are characterized by more rapid upscale growth and smaller temporal variability of perturbation growth than cases with uniform synoptic-scale environments. In the southeastern United States, cases with strong synoptic-scale forcing were found to be insensitive to the scale of IC perturbations, but weakly forced cases show greater sensitivity to small-scale than to large-scale IC perturbations (Weyn and Durrant 2019). All of these studies highlighted the importance of understanding the case dependence of multiscale perturbation evolutions in CPEPS design. However, the case dependence of multiscale perturbation evolutions in CPEPSs in Southern China remains still uncovered. It is unclear if the case dependence of multiscale perturbation evolutions revealed in previous literatures holds for cases in Southern China, since the

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1 The “negative” impacts of adding MO perturbations on ensemble dispersions were defined as “nonlinear impacts” in Z19. However, such a definition was less rigorous, because there may be nonlinear interactions between IC and MO perturbations that still cause “positive impacts” on ensemble dispersion. To illustrate precisely, Z20 has changed the terminology from “nonlinear/linear impacts” to “dispersion reduction/enhancement,” which is also used in this study.
meteorological features of Southern China are particularly unique (Luo 2017; Luo et al. 2020).

Severe weather (especially heavy rainfall) events, which occur in Southern China during the presummer rainy season (April–June), are unique as the production of complicated interactions among multiscale weather systems and are often characterized as “warm-sector rainfall” (Ding 1994; Luo 2017; Luo et al. 2017). Given the low forecast skills and poor predictabilities of heavy rainfall and the lack of operational CPEPSs in Southern China in the presummer rainy season (Zhang et al. 2016; Luo 2017; Luo et al. 2017; Huang and Luo 2017; Du and Chen 2018; Zhang 2018), advancing the CPEPS design for precipitation forecasting in Southern China is a topic worthy of study. As an effort devoted to this objective, Z19 investigated the multiscale characteristics of IC and MO perturbations and their interactions based on 32 cases during the Southern China Monsoon Rainfall Experiment (SCMREX; Luo et al. 2017) and revealed the dispersion reduction for precipitation, which was more evident in events with more moist convections. Based on the same cases as Z19 and Z20 explored the factors related to the setup of perturbation methods that are closely associated with the occurrence of such dispersion reduction, revealed the sensitivities of the magnitude of such dispersion reduction to perturbation methods, and discussed how to use the dispersion reduction to improve precipitation forecasting. For an experimental CPEPS where forecast errors have been underestimated by IC perturbations in approximately 90% of cases (i.e., in 29 out of 32 forecasts), both Z19 and Z20 showed that the dispersion reduction can be applied to improve precipitation forecasting. However, the dependence of such dispersion reduction on severe weather cases with different synoptic-scale forcings during SCMREX has yet to be investigated. This work thus examines this based on heavy-rainfall cases during SCMREX to increase the understanding of multiscale and multiresource interactions in CPEPSs. Conclusions of this work could be expected to contribute to improved CPEPS designs for precipitation forecasting in Southern China.

The remainder of this paper is organized as follows. The configurations of the CPEPS and the experimental design are described in section 2. The case classification is presented in section 3 where two case studies are also outlined, and the experimental results are presented in section 4. Conclusions of this paper and further discussion are illustrated in section 5.

### 2. Model configurations and experimental design

#### a. CPEPS configuration

GM-CPEPS (Zhang 2018) is used in this study (Table 1). GM-CPEPS includes one control member (CN) and 16 perturbed members based on GRAPES-MARS3KM (Zhang et al. 2016), which is a convection-permitting model developed from the Global/Regional Assimilation and Prediction System (GRAPES; Xue and Liu 2007; Chen et al. 2008). Each perturbed member is produced by adding perturbations to the IC, MO, and LBCs of CN. Given that only IC and MO perturbations are the focus herein, the corresponding perturbation methods are simply introduced below. A detailed description of the configurations of GM-CPEPS, especially all the perturbation methods used, is given in Zhang (2018).

IC perturbations are composed of perturbations from the downsampling (DSC), ensemble of data assimilation (EDA), and time-lagged (TLA) schemes (Table 1). In GM-CPEPS, forecast perturbations of EDA generally suffered from smaller dispersion reduction when MO perturbations were added, compared with those of DSC or TLA (Z20). Thus, to simplify the interpretation of the results, EDA perturbations are not separately discussed in this study. DSC perturbations are derived from a mesoscale ensemble prediction system with a resolution of approximately 9 km by subtracting the ensemble mean of 16 perturbed forecasts from each perturbed forecast and then interpolating to the GRAPES-MARS3KM domain. A set of successive CN forecasts valid at different ranges but at similar times is used to generate 16 time-lagged members, the ensemble mean of which is subtracted from each time-lagged member to calculate TLA perturbations. Specifically, to calculate TLA perturbations valid at 0000 UTC, the CN forecasts initialized at 0000, 1200, and 2100 UTC on the previous day, and at 0000 UTC are used.

MO perturbations are generated by combining the SPPT (Bouttier et al. 2012), multiphysics (MP; Xue et al. 2007), and perturbed parameters (PP; Gebhardt et al. 2011) schemes (Table 1). In the SPPT scheme, a random field $r$ drawn from a Gaussian distribution with zero mean is produced during model integration, and the total parameterized tendency of physical processes is then multiplied at each time step by $f = 1 + r$ to form a perturbed tendency. In the MP scheme, four combinations of physics packages for parameterizing the

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**Table 1. Acronyms for the configuration of GM-CPEPS. The acronyms in italics indicate the perturbation methods used to design GM-CPEPS.**

<table>
<thead>
<tr>
<th>GRAPES-MARS3KM</th>
<th>GRAPES–Mesoscale Atmospheric Regional model for South China with resolution of 3 km</th>
</tr>
</thead>
<tbody>
<tr>
<td>GM-CPEPS</td>
<td>CPEPS based on GRAPES-MARS3KM</td>
</tr>
<tr>
<td>CN</td>
<td>The control (deterministic) member</td>
</tr>
<tr>
<td>DSC</td>
<td>Downsampling</td>
</tr>
<tr>
<td>EDA</td>
<td>Ensemble of data assimilation</td>
</tr>
<tr>
<td>TLA</td>
<td>Time-lagged scheme</td>
</tr>
<tr>
<td>SPPT</td>
<td>Stochastically perturbed parameterization tendency</td>
</tr>
<tr>
<td>MP</td>
<td>Multiphysics</td>
</tr>
<tr>
<td>PP</td>
<td>Perturbed parameters</td>
</tr>
<tr>
<td>PPMP</td>
<td>Combination of PP and MP</td>
</tr>
</tbody>
</table>

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Table 2. Setup of the ensemble forecast experiments. All experiments are made of 16 perturbed members with identical LBCs. The names of experiments in boldface, italic, and both italic and boldface indicate the experiments including IC, MO, and both MO and IC perturbations, respectively.

<table>
<thead>
<tr>
<th>Expt</th>
<th>IC perturbations</th>
<th>MO perturbations</th>
</tr>
</thead>
<tbody>
<tr>
<td>ICp</td>
<td>DSC + EDA + TLA</td>
<td>—</td>
</tr>
<tr>
<td>DSC</td>
<td>DSC</td>
<td>—</td>
</tr>
<tr>
<td>TLA</td>
<td>TLA</td>
<td>—</td>
</tr>
<tr>
<td>MOp</td>
<td>—</td>
<td>SPPT + PPMP</td>
</tr>
<tr>
<td>SPPT</td>
<td>—</td>
<td>SPPT</td>
</tr>
<tr>
<td>PPMP</td>
<td>—</td>
<td>PPMP</td>
</tr>
<tr>
<td>ICpMOp</td>
<td>As in ICp</td>
<td>As in MOp</td>
</tr>
<tr>
<td>ICpSPPT</td>
<td>As in ICp</td>
<td>SPPT</td>
</tr>
<tr>
<td>ICpPPMP</td>
<td>As in ICp</td>
<td>PPMP</td>
</tr>
<tr>
<td>DSCMOp</td>
<td>DSC</td>
<td>As in MOp</td>
</tr>
<tr>
<td>TLAMOp</td>
<td>TLA</td>
<td>As in MOp</td>
</tr>
</tbody>
</table>

microphysics and PBL processes are constructed based on the WRF single-moment 6-class (WSM6) and 5-class (WSM5) microphysics schemes (Hong et al. 2004), as well as the medium-range forecast (MRF; Hong and Pan 1996) and the Yonsei University (YSU; Hong et al. 2006) PBL schemes. In the PP scheme, both the rain intercept parameter in the microphysics scheme and the critical Richardson number in the PBL scheme are perturbed by modifying their default values. The combination of PP and MP (PPMP in Table 1) instead of PP or MP is discussed in this study.

b. Experimental design

The purpose of this study is to examine the case dependence of the multiscale interactions between IC and MO perturbations explored by Z19 based on 32 cases. For this reason, 32 12-h ensemble forecasts, which corresponded to cases with different synoptic-scale forcings and had been carried out based on GM-CPEPS without LBC perturbations (i.e., ICpMOp in Z19), are compared with each other. In experiment ICp, all types of perturbations (i.e., DSC, EDA, and TLA) were included in ensemble forecasts; while in experiment MOp, the combination of SPPT and PPMP was included in ensemble forecasts (Table 2). Table 3 elaborates on the configurations of each ensemble member of ICp, MOp, and ICpMOp.

Additionally, it was found in Z20 that the multiscale characteristics of IC and MO perturbations and their interactions are sensitive to the method used to generate IC or MO perturbations. Therefore, the case dependence of the sensitivity of multiscale interactions between IC and MO perturbations to perturbation methods are also examined in this study in additional experiments. These experiments were implemented in the same way as ICpMOp except with different perturbations used in constructing ensembles (Table 2). The comparison between DSC and TLA revealed the sensitivities to IC perturbation methods, which are characterized by different vertical structures but similar low-level magnitudes between DSC and TLA (Z20). The sensitivities of multiscale characteristics of MO perturbations to perturbation methods were investigated by comparing SPPT with PPMP. The differences of forecast perturbations between DSCMOp and DSC and those between TLAMOp and TLA are compared with each other to investigate the sensitivities of multisource-perturbation interactions to IC perturbation methods, while the differences of forecast perturbations between ICpSPPT and ICp and those between ICpPPMP and ICp are compared with each other to investigate the sensitivities to MO perturbation methods.

Table 3. Ensemble-member specifications for different experiments in terms of IC (column 2), the microphysics (column 3), and PBL (column 4) schemes and the rain intercept parameter (Nc, column 5) and the critical Richardson number (Ri, column 6). “A” in column 2 indicates the analyses of CN, while “p1,” “p2,” . . . , “p16” indicate the perturbations from a combination of DSC, EDA, and TLA. The names of experiments in boldface, italic, and both italic and boldface, compose the ICp, MOp, and ICpMOp ensembles, respectively. All the perturbed members use the same LBCs as CN.

<table>
<thead>
<tr>
<th>Member</th>
<th>IC</th>
<th>Microphysics</th>
<th>PBL</th>
<th>Nc (m⁻³)</th>
<th>Ri</th>
</tr>
</thead>
<tbody>
<tr>
<td>CN</td>
<td>A/A/A</td>
<td>WSM6/WSM6/WSM6</td>
<td>MRF/MRF/MRF</td>
<td>8 × 10⁶</td>
<td>0.5/0.5/0.5</td>
</tr>
<tr>
<td>1</td>
<td>A+p1/A+A+p1</td>
<td>WSM6/WSM6/WSM6</td>
<td>MRF/MRF/MRF</td>
<td>8 × 10⁶</td>
<td>0.5/0.5/0.5</td>
</tr>
<tr>
<td>2</td>
<td>A+p2/A+A+p2</td>
<td>WSM6/WSM6/WSM6</td>
<td>MRF/MRF/MRF</td>
<td>8 × 10⁶</td>
<td>0.5/0.5/0.5</td>
</tr>
<tr>
<td>3</td>
<td>A+p3/A+A+p3</td>
<td>WSM6/WSM6/WSM6</td>
<td>MRF/MRF/MRF</td>
<td>8 × 10⁶</td>
<td>0.5/0.5/0.5</td>
</tr>
<tr>
<td>4</td>
<td>A+p4/A+A+p4</td>
<td>WSM6/WSM6/WSM6</td>
<td>MRF/MRF/MRF</td>
<td>8 × 10⁶</td>
<td>0.5/0.5/0.5</td>
</tr>
<tr>
<td>5</td>
<td>A+p5/A+A+p5</td>
<td>WSM6/WSM6/WSM6</td>
<td>MRF/YSU/YSU</td>
<td>8 × 10⁶</td>
<td>0.5/0.5/0.5</td>
</tr>
<tr>
<td>6</td>
<td>A+p6/A+A+p6</td>
<td>WSM6/WSM6/WSM6</td>
<td>MRF/YSU/YSU</td>
<td>8 × 10⁶</td>
<td>0.5/0.5/0.5</td>
</tr>
<tr>
<td>7</td>
<td>A+p7/A+A+p7</td>
<td>WSM6/WSM6/WSM6</td>
<td>MRF/YSU/YSU</td>
<td>8 × 10⁶</td>
<td>0.5/0.5/0.5</td>
</tr>
<tr>
<td>8</td>
<td>A+p8/A+A+p8</td>
<td>WSM6/WSM6/WSM6</td>
<td>MRF/YSU/YSU</td>
<td>8 × 10⁶</td>
<td>0.5/0.5/0.5</td>
</tr>
<tr>
<td>9</td>
<td>A+p9/A+A+p9</td>
<td>WSM6/WSM5/WSM5</td>
<td>MRF/MRF/MRF</td>
<td>8 × 10⁶</td>
<td>0.5/0.5/0.5</td>
</tr>
<tr>
<td>10</td>
<td>A+p10/A+A+p10</td>
<td>WSM6/WSM5/WSM5</td>
<td>MRF/MRF/MRF</td>
<td>8 × 10⁶</td>
<td>0.5/0.5/0.5</td>
</tr>
<tr>
<td>11</td>
<td>A+p11/A+A+p11</td>
<td>WSM6/WSM5/WSM5</td>
<td>MRF/MRF/MRF</td>
<td>8 × 10⁶</td>
<td>0.5/0.5/0.5</td>
</tr>
<tr>
<td>12</td>
<td>A+p12/A+A+p12</td>
<td>WSM6/WSM5/WSM5</td>
<td>MRF/MRF/MRF</td>
<td>8 × 10⁶</td>
<td>0.5/0.5/0.5</td>
</tr>
<tr>
<td>13</td>
<td>A+p13/A+A+p13</td>
<td>WSM6/WSM5/WSM5</td>
<td>MRF/MRF/MRF</td>
<td>8 × 10⁶</td>
<td>0.5/0.5/0.5</td>
</tr>
<tr>
<td>14</td>
<td>A+p14/A+A+p14</td>
<td>WSM6/WSM5/WSM5</td>
<td>MRF/MRF/MRF</td>
<td>8 × 10⁶</td>
<td>0.5/0.5/0.5</td>
</tr>
<tr>
<td>15</td>
<td>A+p15/A+A+p15</td>
<td>WSM6/WSM5/WSM5</td>
<td>MRF/MRF/MRF</td>
<td>8 × 10⁶</td>
<td>0.5/0.5/0.5</td>
</tr>
<tr>
<td>16</td>
<td>A+p16/A+A+p16</td>
<td>WSM6/WSM5/WSM5</td>
<td>MRF/MRF/MRF</td>
<td>8 × 10⁶</td>
<td>0.5/0.5/0.5</td>
</tr>
</tbody>
</table>
c. Analysis method

Verifications of the 1-h accumulated quantitative precipitation forecast (QPF) for both CN and the probabilistic guidance from 16 perturbed members were conducted to investigate differences in forecast performance of precipitation among different cases or different ensemble configurations. As in Z19, precipitation observation data from the surface meteorological stations and automatic weather stations, as well as precipitation analysis data from the U.S. National Oceanic and Atmospheric Administration (NOAA) Climate Precipitation Center Morphing Technique (CMORPH) merged with the rain gauge observations in China (Shen et al. 2014) were used as precipitation observations. For CN, the root-mean-square error (RMSE) was calculated. For probabilistic guidance, the continuous ranked probability score (CRPS; Hersbach 2000) was calculated. In particular, the relative changes in CRPS (ΔCRPS) for a particular experiment with respect to another experiment were discussed here to investigate the differences in QPFs among various experiments, as in Montmerle et al. (2018) and Caron et al. (2019). Specifically, the negative and positive ΔCRPS indicates improved and degraded QPFs of the particular experiment over another experiment, respectively. All the above measures were averaged over the analysis domain ranging from 20° to 26°N and from 106° to 117°E (Fig. 1), which is defined to include the main region of precipitation throughout 12-h forecasts.

As in Johnson et al. (2014), CN precipitation energy is defined as the square of the 1-h accumulated rainfall of CN forecasts; and the CN forecast error energy of precipitation (CNerror), which is defined as the square of precipitation differences between CN forecasts and observations, is used to evaluate the performances of various perturbation methods in estimating forecast errors. Following Johnson et al. (2014), the forecast perturbations are defined as the differences between CN forecasts and perturbed forecasts. This study calculated the precipitation perturbation energy (PPE) and perturbation kinetic energy (PKE) with PPE mainly focused on. As in Z19, PPE and PKE were, respectively, expressed as follows:

\[
PPE = \int_S R^2 \, ds,
\]

and

\[
PKE = \frac{1}{2} \int_{p_0}^{p_1} \int_S (U'^2 + V'^2) \, ds \, dp,
\]

where \(R\), \(U\), and \(V\) denote the perturbations for precipitation, zonal, and meridional velocity, respectively; and \(\int_S\) and \(\int_{p_0}^{p_1}\) denote horizontal and vertical integrations, respectively. Here, \(S\) indicates the analysis domain, while \(p_0\) and \(p_1\) indicate the vertical levels. Both PPE and PKE were averaged over all 16 perturbed members and the analysis domain. Following Z19, the two-dimensional spectral decomposition based on the discrete cosine transform (DCT; Denis et al. 2002) was used to decompose PPE, PKE or CNerror into components at meso-β scales (20–200 km) and those at meso-α scales (200–1300 km).

As in Z19, the multiscale interactions between IC and MO perturbations are discussed in this study based on the PPE differences between ensembles with IC/MO perturbations (e.g., ICpMOp) and those merely with IC perturbations (e.g., ICp), with the positive and negative PPE differences indicating the occurrence of dispersion enhancement and reduction due to adding MO perturbations to IC perturbations, respectively.
Moreover, given the importance of “saturation value”\(^2\) of MO perturbations in interpreting the dispersion reduction (Z19), the saturation value is also investigated here. Because the true saturation values are hard to be calculated in this study based on limited forecast data, the maximum value of meso-\(\beta\)-scale PPE of MO perturbations during the entire 12-h forecasts was used to roughly estimate the saturation value as in Z19.

For the comparison of metrics, including CN precipitation energy, CNerror, \(\Delta\text{CRPS}\), and the differences in PPE, dispersion reduction/enhancement, and \(\Delta\text{CRPS}\) between different experiments, statistical significances of the differences between cases with different forcings were assessed using a bootstrap resampling procedure. Specifically, random samples of these metrics were generated with replacement, and then the differences of metrics between the paired samples from the strongly and weakly forced cases, respectively, were calculated. This procedure was repeated 1000 times and bootstrapping was performed on the metric differences. The rank at which the resampled metric differences crossed zero was used as the significance level (Davis et al. 2010). A 90% significance level was used herein, which indicates a 90% probability that two given metrics differ.

### 3. Case selection

All the experiments were carried out during 8–23 May 2014, when SCMREX was implemented and significant heavy rainfall events characterized by different synoptic-scale forcings occurred (Luo et al. 2017). In the experimental period, 32 12-h forecasts initialized at 0000/1200 UTC, which responded to 32 cases, were collected. These cases were discriminated in terms of the strength of synoptic-scale forcing and some of them were selected to examine the differences in multiscale characteristics of perturbation energy based on IC and MO perturbations and their interactions during different cases, which also have different synoptic-scale forcings.

#### a. Case classification

In this study, cases were classified based on a combination of synoptic situation comparisons and synoptic-scale forcing diagnostics.\(^3\) The 0.5° × 0.5° Global Forecast System (GFS) analysis data at the initial times of ensemble forecasts were used to illustrate the synoptic situation (Fig. 1) and the presence of synoptic systems (e.g., jets and troughs) was used to identify the synoptically forced cases. To quantitatively diagnose the strength of synoptic-scale forcing, four measures were calculated based on the GFS data over the analysis domain. These measures included 200-hPa divergence, 250–850-hPa differential vorticity advection, and 850-hPa temperature advection, which have also been used in Jankov and Gallus (2004), Duda and Gallus (2013), and Weyn and Durran (2019), and low-level jet intensity. Low-level jets have been confirmed by many recent studies to be a key synoptic-forcing factor regulating the heavy rainfall in Southern China.

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\(^2\)Given that saturations of PPE are discussed only at meso-\(\beta\) scales, the expression of “meso-\(\beta\)-scale” is omitted in the following illustrations related to the saturation value of PPE, for brevity.

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\(^3\)The convective-adjustment time scale \(\tau_c\) (Done et al. 2006) was also calculated for cases in this study and showed smaller values in cases with stronger synoptic-scale forcing. Such result was consistent with that in some previous works (e.g., Keil et al. 2014; Surcel et al. 2016). However, \(\tau_c\) is actually a measure of differentiating between equilibrium and nonequilibrium cases and can only be considered as a loose indication of strong- or weak-synoptic-forcing cases (Surcel et al. 2017). So, the result of \(\tau_c\) is not used here.
during the presummer rainy season (e.g., Du and Chen 2019; Li et al. 2020). The low-level jet intensity is thus considered as one of the synoptic forcing measures and was calculated as follows. First, the criteria of Du and Chen (2019) were used to identify the area with low-level jets as: 1) the maximum wind speed was greater than 10 m s$^{-1}$ below 700 hPa; and 2) below 600 hPa, the wind speed must decrease by at least 3 m s$^{-1}$ from the height of the wind maximum to the wind minimum above that. Second, the low-level jet intensity is defined as the sum of wind speed below 600 hPa over areas with low-level jets. For the above four measures, larger values correspond to stronger synoptic-scale forcing.

The case classification was similar to that of Jankov and Gallus (2004) and Duda and Gallus (2013). First, the magnitudes of all four measures were ranked for all the 32 cases (Fig. 2) such that the strongest and weakest values in each category were given a rank of 1 and 32, respectively. Then, the ranks of each measure were summed and the 10 cases with the lowest and highest sums were considered to be strongly and weakly forced, respectively (Fig. 2).

Following Jankov and Gallus (2004), the remaining 12 cases were actually considered to be moderately forced but not discussed to avoid the dilution of case-dependent characteristics.
b. Case study overview

Two 12-h ensemble forecasts with initial times of 0000 UTC 11 May and 0000 UTC 8 May (hereafter cases 1 and 2, respectively) were selected to intuitively demonstrate the representative characteristics of perturbation energy and QPF in the strongly and weakly forced cases, respectively. For these two cases, the detailed descriptions can be found in Luo et al. (2017) and Huang and Luo (2017) and overviews are provided here.

Double low-level jets in the southwesterly flow, one located at 850–700 hPa and the other located at 925 hPa, were observed at 0000 UTC 11 May (Fig. 1a). The formation of a low-level jet above the PBL is attributed to pressure gradient forces induced by midlatitude cyclones, while that of a low-level jet in the PBL is related to the joint effects of diurnal thermal forcing over sloping terrain and diurnally varying boundary layer friction (Du et al. 2015). Moreover, a low-level shear line moved southeastward during the 12-h period of study, accompanied by the eastward movement of a midlevel trough. Evidently, case 1 was characterized by strong synoptic-scale forcing. This conclusion was consistent with the relatively large synoptic-scale forcing measures (Fig. 2). For case 1, there were two mesoscale convective systems (i.e., CS1 and CS2 in Fig. 3a) in eastern Guangxi (GX) and the coastal region of Guangdong (GD) in the first few hours, respectively. CS1 was closely related to the 850-hPa low-level jet and shear line, while CS2 formed locally under the influence of the interaction between the 925-hPa low-level jet and coastline terrain in a warm and moist environment (Du and Chen 2018; Liu et al. 2018). In the next few hours, CS1 moved southeastward into GD, while CS2 moved north-eastward along the GD coastline with new convections continuously initiating at its southwestern periphery, which led to the formation of CS3 (Fig. 3b). CS1 gradually approached CS3 during the following few hours and merged with CS3 (i.e., CS in Fig. 3c).

The initial upper-level flow at 0000 UTC 8 May was characterized by nearly zonal 500-hPa heights with a ridge over the north of Southern China, while at lower levels, GX, GD, and Hainan (HN) were dominated by weak southwesterly flows (Fig. 1b). At heights below 850 hPa, the southerly and southeasterly winds formed a convergence zone in the offshore area of GD, which gradually approached the coastal region of GD in the next 12 h (not shown). Thus, the synoptic-scale forcing for case 2 was weak, given the lack of low-level jets or troughs. And the relatively small synoptic-scale forcing measures further demonstrated the synoptic feature of weak forcing (Fig. 2). For case 2, some small-scale convective clusters were observed around the southwestern coastal region of Southern China and the offshore area of GD in the first few hours (Fig. 3d), which moved northeastward and northwestward in the next few hours, respectively. Such convective clusters developed in southeastern GX and the coastal region and offshore sea of GD in a convectively unstable environment and formed two convective systems (i.e., CS1 and CS2 in Fig. 3e). Then, both CS1 and CS2 intensified and grew upscale, organizing into a quasi-linear mesoscale convective system (i.e., CS in Fig. 3f) over GD.

4. Results

a. Multiscale characteristics of CN forecasts

The comparison of CN precipitation energy between the strongly and weakly forced cases (cf. solid and dashed black curves in Fig. 4) indicates that the cases with stronger forcing are characterized by larger precipitation energy. Such behavior was also found in some previous works (Keil et al. 2014; Surcel et al. 2016) and was more statistically significant at meso-α than meso-β scales (cf. black dots in Fig. 4). Thus, the synoptic-scale forcing is more favorable for the occurrence of larger-coverage precipitation.
Given the definition of CNerror, forecast errors in the location of precipitation greatly contributed to CNerror (Fig. 3). Due to larger coverages of precipitation, CN forecasts of the cases with stronger forcing were penalized more for location errors. Such result can be intuitively evidenced in Fig. 3. Specifically, compared with case 2, case 1 showed larger RMSEs before 6 h when precipitation coverages were larger but showed comparable RMSEs beyond 6 h when precipitation coverages were comparable. Thus, it should be expected that CNerror was larger in the strong- than weak-forcing cases especially at meso-α scales (Fig. 4).

Note that CRPS showed similar behaviors in terms of evolution with precipitation coverages as RMSE (Fig. 3), because both CRPS and RMSE are gridpoint-based scores. Thus, CRPSs were generally larger in the strong- than weak-forcing cases.

b. Multiscale characteristics of forecast perturbations

1) DIFFERENT SOURCES OF PERTURBATIONS

Figures 5a and 5b show the evolution of PPE, which is averaged over all 16 perturbed members. For both ICp and MOp, PPE was larger in the strong- than weak-forcing cases in nearly the entire 12-h forecasts at meso-α scales and beyond 3 h at meso-β scales (cf. solid and dashed curves in Figs. 5a,b). This result corroborates the conclusion of recent studies (Nielsen and Schumacher 2016; Klasa et al. 2019) that the synoptic-scale forcing favors perturbation growth. This is probably related to the more moist convection, which is more conducive to perturbation growth, in the cases with stronger forcing.

As shown in Figs. 5a and 5b, MOp PPE was closer to ICp PPE in the weak- than strong-forcing cases. This illustrates a result that MO perturbations may exert more influence on PPE.
in the weak- than strong-forcing cases, which is consistent with the results of some past studies (e.g., Keil and Craig 2011; Keil et al. 2014). The result that MO perturbations show more influence in the weak- than strong-forcing cases was more statistically significant at meso-α than meso-β scales, probably because the impact of synoptic-scale forcing is greater at larger scales but the impact of MO perturbations is larger at smaller scales. At meso-β scales, the positive differences between the ICp PPE (black curves) and the saturation value of MOp PPE (green lines) in the 5–9-h forecasts were smaller in the weak- than strong-forcing cases (Fig. 5b).

Figures 5c and 5d show the ratio of PPE to CNerror, while Fig. 5e shows ΔCRPS for the probabilistic forecasts based on 16 perturbed members. At meso-α scales, for ICp, forecast

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Fig. 6. Vertical profiles at the (a) initial time and (b) evolution of the meso-α-scale PKE for DSC (red) and TLA (blue). PKE is averaged over all 16 perturbed members and the analysis domains. In (b), PKE is averaged over the levels from 1000 to 700 hPa. The strongly and weakly forced cases are shown in solid and dashed curves, respectively.

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Fig. 7. As in Fig. 5, but for experiments using different IC perturbation methods.
errors were underestimated in all cases for ICp and MOp, with more serious underestimations for MOp in the stronger-forced cases (Fig. 5c). The meso-β-scale forecast errors were overestimated and underestimated in all cases for ICp and MOp, respectively (Fig. 5d). Compared with the weakly forced cases, the strongly forced cases showed larger underestimations for MOp and smaller overestimations for ICp. Thus, the improvements of ICp over MOp in estimating forecast errors were more evident in the cases with stronger forcing at all scales, leading to larger improvements of ICp over MOp in QPFs, which was indicated by negative ΔCRPSs, in the stronger-forced cases (Fig. 5e). In particular, the result that the QPF improvements of ICp over MOp were larger in the strongly-forced cases was statistically significant in 7 out of 12 lead times.

2) DIFFERENT METHODS OF IC PERTURBATIONS

At the initial time, for DSC, the meso-α-scale PKE generally showed similar vertical structures but different magnitudes between the strongly and weakly forced cases; while for TLA, the meso-α-scale PKE differed between the strongly and weakly forced cases largely above 400 hPa (Fig. 6a). This indicates that the initial meso-α-scale PKE at lower levels is less sensitive to synoptic-scale forcing in TLA than DSC, leading to smaller differences in PKE evolution between the strongly and weakly forced cases in TLA than DSC (Fig. 6b). Thus, before 8 h, the meso-α-scale PKE at lower levels showed larger magnitude differences between DSC and TLA in the weakly than strongly forced cases (Fig. 6b).

Consistent with the low-level PKE, PPE generally showed larger differences between TLA and DSC in the weakly than strongly forced cases especially at meso-α scales before 8 h (Figs. 7a,b). As such, the improvements of TLA over DSC in estimating the meso-α-scale forecast errors were more evident in the weak- than strong-forcing cases while the degradations of TLA over DSC in estimating the meso-β-scale forecast errors were comparable between both cases (Figs. 7c,d). The QPF improvements of TLA over DSC in estimating the meso-α-scale forecast errors were comparable between both cases (Figs. 7c,d). The ΔCRPS differences shown in Fig. 7e between the weakly and strongly forced cases were only statistically significant at four lead times, although such ΔCRPS differences were overall comparable with those shown in Fig. 5e where ICp was compared with MOp.

3) DIFFERENT METHODS OF MO PERTURBATIONS

Consistent with the magnitudes of PPE, the saturation values of PPE were greater in the cases with stronger forcing for both PPMP and SPPT (Fig. 8b). This may be related to the result that the synoptic-scale forcing favors PPE growth and deserves further investigations. At all scales, PPE amplifications of PPMP over SPPT were slightly larger in the cases with stronger forcing after the first few hours (Figs. 8a,b). This is attributed to the result that the synoptic-scale forcing favors
PPE growth was more prominent in PPMP than SPPT, which is probably related to no tendency perturbations applied near the surface in SPPT (Zhang 2018). This leads to slightly larger increases in saturation values of PPE of PPMP over SPPT in the strongly than weakly forced cases (Fig. 8b). However, PPE amplifications of PPMP over SPPT were not statistically significant at all scales. Thus, the improved estimations of forecast errors in PPMP over SPPT were overall comparable between the strongly and weakly forced cases (Figs. 8c,d). The larger D\textsubscript{CRPS} for PPMP with respect to SPPT in the cases with weaker forcing (Fig. 8e) were attributed to the smaller CRPS in those cases.

c. **Multiscale interactions of multisource perturbations**

1) **Different sources of perturbations**

Figures 9a and 9b show the difference in PPE between ICpMOp and ICp, which is averaged over all 16 perturbed members. The dispersion reduction due to adding MOp perturbations to ICp, which is indicated by curves with negative values in Figs. 9a and 9b, was present at all scales, with larger dispersion reduction in the strongly than weakly forced cases especially at meso-\(\alpha\) scales. This conclusion is intuitively shown in Figs. 10a and 10b, where the negative PPE differences between ICpMOp and ICp (dashed contours and blue shading) were evidently broader and greater in case 1 than case 2.

Z20 stated that the larger PPE magnitudes of IC perturbations and the smaller saturation values (or magnitudes) of PPE of MO perturbations boost the dispersion reduction. This statement can be evidenced in Fig. 10: the areas with larger meso-\(\beta\)-scale dispersion reduction (darker blue shading in Figs. 10a,b) were generally consistent with the areas where the meso-\(\beta\)-scale PPE differences between ICp and MOp were larger (darker red shading in Figs. 10c,d). Thus, the larger PPE differences at meso-\(\beta\) scales between ICp and MOp in the strongly (e.g., case 1) than weakly (e.g., case 2) forced cases, as intuitively shown in the comparison of red shading between Figs. 10c and 10d, explain why the cases with stronger forcing showed larger meso-\(\beta\)-scale dispersion reduction.

The faster PPE saturations of MO perturbations, which can be accelerated more evidently by the larger enhancements of convective activities relative to CN due to IC perturbations, also boost the dispersion reduction (Z20). This concept is evidenced by the behavior that the areas where enhancements of convective activities relative to CN due to IC perturbations were larger (black contours in Figs. 10c,d), were characterized by larger meso-\(\beta\)-scale dispersion reduction.

![Fig. 9](image-url)  
Fig. 9. As in Fig. 5, but for (a),(b) the difference in PPE between ICpMOp and ICp. The black dots on the upper axes of (a) and (b) indicate the lead times when the PPE differences between ICpMOp and ICp are significantly different between the cases with strong and weak forcing, with the significance level exceeding 90%.
The areas with enhancements of convective activities relative to CN due to IC perturbations were larger in the strongly (e.g., case 1) than weakly (e.g., case 2) forced cases, as intuitively shown in the comparison of black contours between Figs. 10c and 10d. Moreover, such areas seemed to be located farther from the areas with moist convection of CN (green contours in Figs. 10c,d) in the strongly (e.g., case 1) than weakly (e.g., case 2) forced cases. Thus, the effects of IC perturbations on strengthening and spreading moist convection of CN and thereby on the enhancements of convective activities relative to CN are more significant in the background flow with stronger forcing. As such, the cases with stronger forcing have more potential for promoting saturations of MO perturbations and thus have larger areas with meso-β-scale dispersion reduction.

The net impacts of adding MO perturbations on the meso-α-scale PPE is a combination of dispersion enhancement, which can be boosted when the meso-α-scale PPE of MO perturbations is closer to that of IC perturbations, and dispersion reduction, which results from the upscale growth of saturated meso-β-scale MO perturbations (Z20). This concept is illustrated by comparisons of the dispersion enhancement and reduction at meso-α scales between cases 1 and 2 (contours in Figs. 10a,b). In case 1, the larger meso-α-scale dispersion reduction was concentrated in areas with larger meso-β-scale dispersion reduction and represents the upscale growth of saturated MO perturbations. In contrast, in case 2, the smaller meso-β-scale dispersion reduction, as well as the closer PPE magnitude between MO and IC perturbations at meso-α scales, resulted in a more balanced field of dispersion reduction/enhancement at meso-α scales. Thus, the meso-α-scale dispersion reduction was larger in the strongly (e.g., case 1) than weakly (e.g., case 2) forced cases.

The dispersion reduction due to adding MO perturbations to ICp aggravated the underestimation of meso-α-scale forecast errors in ICp but alleviated the overestimation of meso-β-scale forecast errors in ICp (Figs. 9c,d). Generally, both the degradation and improvement due to the dispersion reduction in estimating forecast errors were comparable between strongly and weakly forced cases. However, because the cases with stronger forcing were characterized by less serious overestimations of the meso-β-scale forecast errors.
in ICp, the dispersion reduction led to a greater risk of underestimating the meso-\(\beta\)-scale forecast errors (Fig. 9d). This concept is intuitively shown in Fig. 11, where the number of perturbed members with precipitation ratio above 10 mm h\(^{-1}\) in the same position is indicated. Ensemble members in ICp were excessively distributed in the areas without observed precipitation due to the overestimation of meso-\(\beta\)-scale forecast errors in both cases 1 and 2 (Figs. 11a,c). Such issue was alleviated in ICpMOp due to dispersion reduction, with more ensemble members distributed in the areas with observed precipitation in ICpMOp than ICp (Fig. 11). However, in case 1, some areas with observed precipitation were covered by ensemble members of ICp but missed by those of ICpMOp (Figs. 11a,b). And such a risk of missing due to dispersion reduction was rare in case 2 (Figs. 11c,d). Thus, it should be expected that QPF improvements due to the dispersion reduction were more statistically significant in weakly than strongly forced cases (Fig. 11e).

2) DIFFERENT PERTURBATION METHODS OF MULTISOURCE INTERACTIONS

Overall, compared with DSCMOp, TLAMOp showed larger dispersion reduction at meso-\(\beta\) scales and smaller dispersion enhancement at meso-\(\alpha\) scales, which were caused by adding MOp perturbations (cf. red and blue curves in Figs. 12a,b). Such result was slightly more evident in the cases with weaker forcing and is consistent with the result illustrated previously that PPE generally showed slightly larger differences between TLA and DSC in the weakly than strongly forced cases. As such, the behavior that the improvements in forecast-error estimation and QPF of TLAMOp over TLA were larger than those of DSCMOp over TLA were only statistically significant at four lead times.
On average, the increases in dispersion reduction of SPPT over PPMP were larger in the cases with stronger forcing (cf. magenta and cyan curves in Figs. 13a,b). This result should be attributed to the behavior illustrated previously that increases in both the meso-α-scale magnitude and saturation value of PPE of PPMP over SPPT were slightly larger in the strongly than weakly forced cases. Accordingly, the behavior that ICpSPPT outperformed ICpPPMP in estimating the meso-β-scale forecast errors were more evident in the strongly than weakly forced cases (Figs. 13c,d). It is thus expected that ICpSPPT showed larger QPF improvements relative to ICp than ICpPPMP in the strongly than weakly forced cases (Fig. 13e).

Figure 14 shows ΔCRPSs for ICpMOp with respect to the other experiments conducted here. Thus, the negative ΔCRPSs indicate the superiority of ICpMOp over the other experiments in QPFs, which has been illustrated in Z20 to be present in all the 32 cases. In fact, the superiority of ICpMOp was case-dependent, with larger superiority in the cases with weaker forcing (Fig. 14). Such a phenomenon was most evident when ICpMOp was compared with the experiments merely using MO perturbations (circles in Fig. 14). In particular, the superiority of ICpMOp over DSCMOp, TLAMOp, ICpSPPT, and ICpPPMP was generally larger in the cases with weaker forcing, as indicated by larger negative ΔCRPSs for both squares and triangles in the right than left column of Fig. 14. These indicate the greater importance of combining various IC and MO perturbation methods in improving the benefits of dispersion reduction in QPFs in the weak- than strong-forcing cases.

5. Conclusions and discussion

Convection-permitting ensemble forecasts of heavy-rainfall cases with different synoptic-scale forcings over Southern China during SCMREX were analyzed in this study, to examine the case dependence of the multiscale characteristics of multisource perturbations and their interactions in CPEPSs, and that of the forecast performances of various ensemble configurations. These cases were classified into two groups: strongly and weakly forced, based on the magnitude of synoptic-scale forcing (i.e., divergence, differential vorticity advection,
temperature advection, and low-level jet intensity), and each group included 10 cases. Moreover, the cases initialized at 0000 UTC 11 May and 0000 UTC 8 May 2014 were used as representative strongly and weakly forced cases, respectively, to intuitively demonstrate the case-dependent results. The focus is on the 12-h evolution of PPE and probabilistic forecasts of precipitation.

The synoptic-scale forcing favors the occurrence of large-coverage precipitation and the growth of forecast errors/perturbations. Thus, both CNerror and PPE of IC or MO perturbations were larger in the cases with stronger forcing, especially at meso- scales. The dispersion reduction was larger in the strong- than weak-forcing cases. This is because the cases with weaker forcing had larger impacts of MO perturbations on the one hand, which led to smaller magnitude differences in PPE between IC and MO perturbations; and the weaker forcing cases had less evident enhancements of convective activities relative to CN due to IC perturbations on the other hand. The cases with weaker forcing generally showed slightly larger and significantly smaller sensitivities of dispersion reduction to the IC and MO perturbation methods, respectively. This is because the PPE magnitude of IC perturbations was more sensitive to perturbation methods in the weaker forcing cases, while the saturation value of PPE of MO perturbations was less sensitive to perturbation methods in the weaker forcing cases.

The advantages of IC perturbations over MO perturbations in the 12-h QPFs were larger in the strongly than weakly forced cases, because forecast errors were more seriously underestimated in MO perturbations in the cases with stronger forcing. Additionally, the QPF improvements due to changing the IC or MO perturbation methods were slightly larger in the cases with weaker forcing.

The overestimations of forecast errors in IC perturbations can be alleviated by the dispersion reduction caused by adding MO perturbations. The benefits of dispersion reduction in improving QPFs were larger in the weakly than strongly forced cases, because the dispersion reduction led to a greater risk of underestimating forecast errors at meso- scales in the cases with stronger forcing. For the strongly forced cases, the benefits of dispersion reduction can be effectively improved by properly selecting the MO perturbation methods; while for the weakly forced cases, combining various IC and MO perturbation methods can be an effective way to improve the benefits of dispersion reduction.

Note that the results presented herein probably depend on the specific CPEPS with specific perturbation methods or on the unique region (i.e., Southern China) in the unique period (i.e., SCMREX) under study. To gain more insight into the case dependence of the impacts of different CPEPS designs, probabilistic forecasts of features related to convective systems, as well as the neighborhood-based ensemble dispersion, will be investigated in following works. Work is also...
progressing to investigate the biases in MO perturbation methods, which may be related to saturation values and should be removed to further improve forecast skill. And the corresponding results are expected to provide more guidance for the CPEPS design in selecting/developing proper MO perturbation methods.

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