A stochastic and nonlinear representation of model uncertainty in a convective-scale ensemble prediction system

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Introduction

Accurately addressing model uncertainties with a consideration of the enhanced effect of nonlinearities in a high resolution convective-scale system is a crucial issue for performing convection-allowing ensemble prediction systems (CAEPSs). In this study, a conditional nonlinear–stochastic perturbation method is developed to simultaneously consider both a stochastic and a nonlinear representation of model uncertainties associated with physics parameterization in the Global and Regional Assimilation and Prediction Enhanced System (GRAPES)-CAEPS with a horizontal resolution of 3 km.

The nonlinear forcing singular vector (NFSV) for a nonlinear representation of model uncertainties and the Stochastically Perturbed Parameterization Tendencies (SPPT) scheme for a stochastic representation of model uncertainties, are applied. Two experiments were carried out over South China for a month (1–30 May 2020), one with a SPPT scheme and the other with a nonlinear–stochastic perturbation using a combination of SPPT and NFSV schemes. The combination of SPPT and NFSV schemes is compared with the SPPT scheme.

Objectives

This study aims to investigate if the combination of SPPT and NFSV schemes is compared with the SPPT scheme to investigate whether the conditional nonlinear–stochastic perturbation method that combines nonlinear and stochastic schemes can represent model uncertainty better than the traditional stochastic SPPT approach.

Methods

- **The NFSV**

The NFSV (Duan and Zhou 2013), is used to identify the optimal nonlinear tendency perturbation which shows the largest nonlinear evolution under a given physical constraint at a given future time. The NFSV f_δ can be calculated by solving the following nonlinear maximization optimization problem, and the solution of the optimization problem is called the NFSV:

$$J_\delta(f_\delta) = \max_{\|f\|_a \le \delta} J(f) = \max_{\|f\|_a \le \delta} \|M_\tau(U_0, f) - M_\tau(U_0, 0)\|_b$$

where $M_\tau(U_0, 0)$ and $M_\tau(U_0, f)$ represent the propagator of the nonlinear model and the propagator of the nonlinear model with a tendency perturbation f, respectively. U_0 is the initial basic state, and τ represents a given future time.

- **The SPPT scheme**

The SPPT scheme perturbs the net parameterization tendencies with temporally and spatially correlated perturbation to represent model uncertainties associated with the physics parameterization (Palmer et al. 2009), whose equation is expressed as follows:

$$X = \psi(\lambda, \phi, t)\hat{X}$$

where $\hat{X}$ and X represent the net tendency term and the perturbed net tendency, respectively. The random perturbation field is denoted by the term $\psi(\lambda, \phi, t)$, which is characterized by the first-order auto-regressive processes with spherical harmonic expansion.

Reference

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Results

- **Horizontal distributions of the calculated NFSV**

Figure 1 shows the horizontal distributions of NFSVs that are obtained using the principal component analysis (PCA)-based particle swarm optimization (PSO) algorithm. We find that for different variables at different heights, the magnitude of the NFSV perturbation is different, and, in general, the NFSV perturbations are relatively scattered for all levels and variables. The calculated NFSVs are then forced on the physical parameterized tendencies of zonal wind, meridional wind, temperature and humidity of the model in the CAEPS.

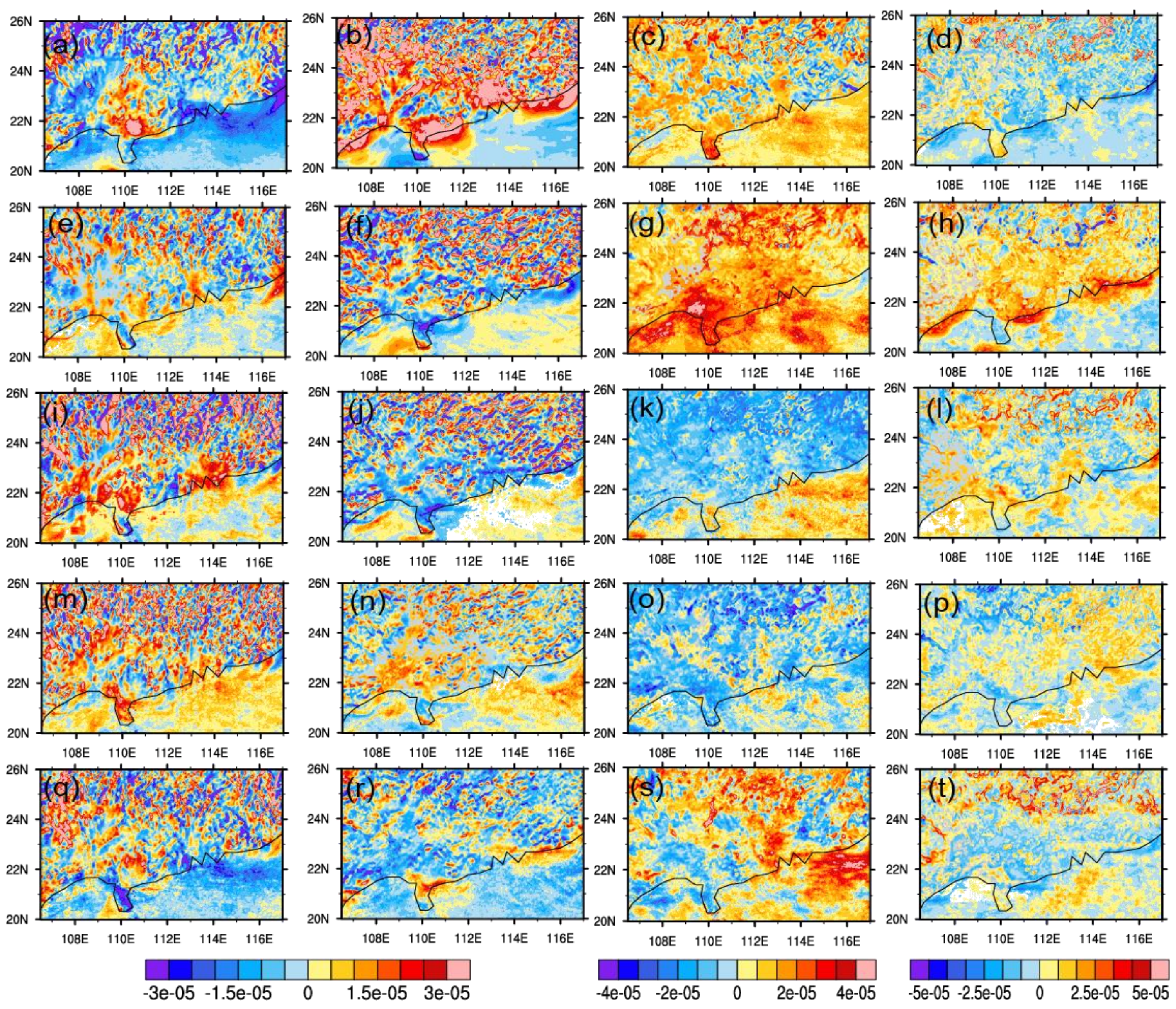

Fig. 1. Horizontal distribution of NFSVs for (a, e, i, m, q) U-tendency, (b, f, j, n, r) V-tendency, (c, g, k, o, s) T-tendency, and (d, h, l, p, t) Q-tendency at (a, b, c, d) 1000 hPa, (e, f, g, h) 850 hPa, (i, j, k, l) 700 hPa, (m, n, o, p) 500 hPa, and (q, r, s, t) 200 hPa.

- **Precipitation verification**

Horizontal distributions of monthly-averaged 24-h accumulated precipitation for the SPPT (Fig. 2a) and SPPT_NFSV (Fig. 2b) experiments are shown. And the observed precipitation shown in Fig. 2d. Comparing and assessing the simulated precipitation of SPPT (Fig. 2a) and SPPT_NFSV experiment (Fig.2b) with the observed precipitation distribution (Fig. 2d), we find that the SPPT_NFSV experiment (Fig. 2b) can better simulate the main concentrated observed precipitation area, and can successfully simulate the center of the precipitation shown in the observed precipitation (Fig. 2d). In addition, the difference in precipitation (Fig. 2c), which is defined as the difference in precipitation of SPPT_NFSV minus that of SPPT, demonstrates that, when compared to the SPPT experiment, the SPPT NFSV experiment can successfully simulate a main concentrated precipitation area that corresponds to the observed precipitation (Fig. 2d). This indicates that the introduction of NFSV perturbation has a beneficial positive impact on the simulation of precipitation and can improve the skills and effects of precipitation simulation.

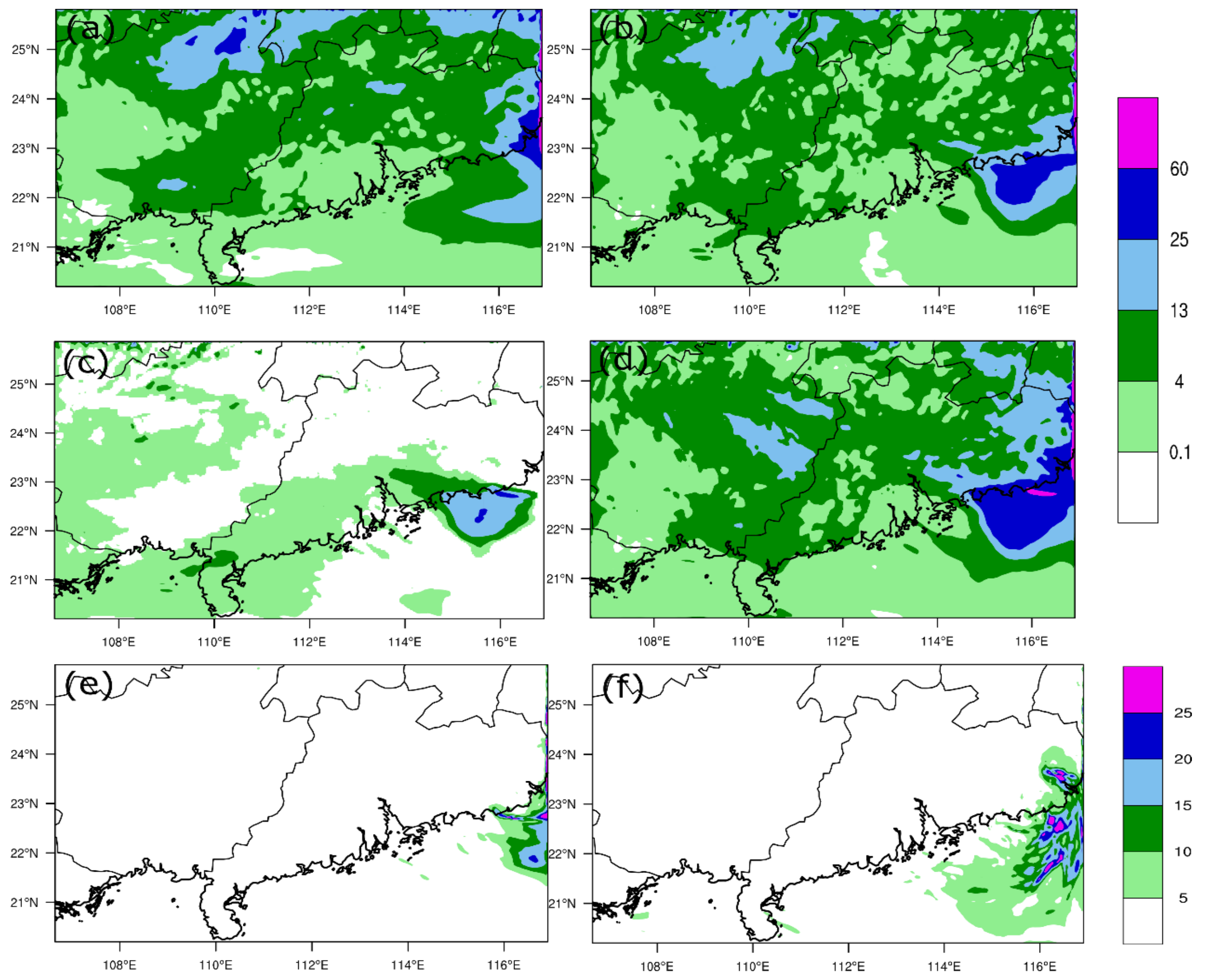

FIG. 2. Horizontal distribution of monthly-averaged 24-h accumulated precipitation for the (a) SPPT and (b) SPPT_NFSV experiments and (c) the difference of precipitation (defined as the precipitation of SPPT_NFSV minus that of SPPT), and (d) the corresponding observed precipitation, as well as the spread of precipitation for (e) the SPPT and (f) the SPPT_NFSV experiments.

- **Verification for upper-air and surface weather variables**

A set of verification measures was employed to assess the upper-air and surface weather variables: The domain-averaged ensemble spread, RMSE, spread-error consistency, CRPS, rank histograms, and outlier scores. The results show that the SPPT_NFSV experiment is capable of increasing the ensemble spread and reducing the RMSE for both surface and upper-air weather variables; therefore, the corresponding consistency is improved. Furthermore, the CRPS, and the rank histogram and outlier score are also improved, which implies that the SPPT_NFSV experiment has a beneficial effect on the overall performance of probabilistic forecasting.

Conclusion

- The combination of SPPT and NFSV schemes can produce more reliable precipitation forecasts, and has a beneficial effect on the overall probabilistic forecasting performance.
- Overall, combining the SPPT and NFSV schemes improves the overall probabilistic skill and has an advantage over the SPPT scheme.
- Adding additional state-independent nonlinear noise may contribute to a more comprehensive characterization of model error for representing model uncertainties in CAEPSs.