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An evaluation of parametric sensitivities of different meteorological variables simulated by the WRF model

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The specification of model parameters in numerical weather prediction (NWP) models has great influence on model performance. However, how to specify model parameters properly is not a trivial task because a typical NWP model like the Weather Research and Forecasting (WRF) model contains many model parameters and many model outputs. This article presents the results of an investigation into the sensitivities of different WRF model outputs to the specification of its model parameters. Using a global sensitivity analysis method, the sensitivities are evaluated for surface meteorological variables such as precipitation, surface air temperature, humidity and wind speed, as well as for atmospheric variables such as total precipitable water, cloud cover, boundary-layer height and outgoing long-wave radiation at the top of the atmosphere, all simulated by the WRF model using different model parameters. The goal of this study is to identify the parameters that exert most influence on the skill of short-range meteorological forecasts. The study was performed over the Greater Beijing Region of China. A total of 23 adjustable parameters from seven different physical parametrization schemes were considered. The results indicate that parameter sensitivities vary with different model outputs. However, some of the 23 model parameters considered are shown to be sensitive to all model outputs evaluated, while other parameters may be sensitive to a particular output. The sensitivity results from this research are a basis for further optimizations of the WRF model parameters.

Key Words: multi-objective sensitivity analysis; global sensitivity analysis; WRF parameter estimation; parametric uncertainty

Received 12 October 2015; Revised 7 July 2016; Accepted 17 July 2016; Published online in Wiley Online Library

1. Introduction

The performance of numerical weather prediction (NWP) models such as the Weather Research and Forecasting (WRF) model is affected by three sources of uncertainties: (i) the representation of model physics, (ii) the specification of initial and lateral boundary conditions, and (iii) the specification of model parameters (i.e. the coefficients and exponents in model equations). In order to improve model performance, all three sources of uncertainty must be quantified and reduced. In literature, there is a lot of attention devoted to creating the most physically realistic model possible (Stensrud, 2007). A good example is the creation of the WRF model, which can be looked at as millions of different individual models on a single platform (Skamarock *et al.*, 2008). For each physical process (related to land surface, planetary boundary and surface layers, microphysics, radiation, and cumulus clouds), the WRF model has many different parametrization schemes to choose from and any feasible combination of those schemes renders a specific version of the WRF model. Several carefully chosen combinations of the WRF model parametrization schemes can be used to generate perturbed-physics ensemble forecasts (Bellprat *et al.*, 2012; Tapiador *et al.*, 2012). Data assimilation techniques are regarded as one of the most effective ways to improve NWP forecasting performance in recent years. It works through mathematical operations that merge model simulations and observations to create the initial model states most consistent with the observations (Evensen, 1997; Kalnay, 2003). There exist many data assimilation methods (e.g. 3D-Var, 4D-Var, Ensemble Kalman Filter, etc.) that have been adopted in operational NWP forecasting systems and have been shown to play a critical role in improving model performance (Wang *et al.*, 2008; Huang *et al.*, 2009). However, better physical representation and data assimilation alone are not sufficient to generate accurate and reliable meteorological forecasts (Gao and Chou, 1994). Parameter estimation is another important avenue for improving NWP model performance.

Researchers have been aware of the importance of reducing model parametric uncertainty in improving model performance

(Qiu and Chou, 1987). There are several ways to estimate model parameters. Parameters with clear physical meanings can be determined using observations or by theoretical calculation. Parameter values may also be chosen using a 'trial and error' method (Allen, 1999; Knutti *et al.*, 2002), which is subjective and highly labour intensive, and requires expert knowledge of the model. A more objective way of parameter estimation is to use inverse methods which minimize a cost function measuring the fitness between the model simulations with observations through parameter tuning. Different inverse methods have been used to estimate parameters of NWP models, including the variational methods (Guo *et al.*, 1997; Lea *et al.*, 2000, 2002; Köhl and Willebrand, 2002, 2003) and ensemble Kalman filter (Annan and Hargreaves, 2004; Annan *et al.*, 2005a, 2005b; Schirber *et al.*, 2013). Other inverse methods, such as Markov Chain Monte Carlo (MCMC), Genetic Algorithm (GA), Very Fast Simulated Annealing (VFSA), among others, have also been used to estimate the parameters of NWP and climate models (Jackson *et al.*, 2004; Severijns and Hazeleger, 2005; Villagran *et al.*, 2008; Medvigy *et al.*, 2010; Gregoire *et al.*, 2011; Jarvinen *et al.*, 2012; Solonen *et al.*, 2012; Ollinaho *et al.*, 2013). Those methods generally require a large number of model experiments to identify the optimal parameter sets and thus make their use for optimizing parameters of full-scale NWP models very difficult.

There are several difficulties in estimating NWP model parameters. First, the number of tunable parameters in NWP models is typically large (from tens to >100), and the required number of model experiments for parameter optimization using conventional optimization methods increases exponentially with the growth of parameter dimension, up to 10^4 or more (i.e. the 'curse of dimensionality' problem). Second, NWP models simulate many different meteorological variables such as precipitation, temperature, humidity, atmospheric pressure, wind, among others. Parameter estimation must consider several variables of interest simultaneously (Randall and Wielicki, 1997; Bellprat *et al.*, 2012). Third, NWP models are very expensive to run. Even with today's supercomputers, it is still not computationally affordable to run long periods of NWP model simulations for thousands of times. To address those difficulties, more effective inverse methods must be developed.

There is noteworthy development in new parameter estimation methods for large complex system models like the NWP models. Those methods typically involve two key measures. One measure is to reduce the parameter dimensionality using sensitivity analysis to screen out the insensitive parameters from the sensitive ones so one can focus on estimating parameters that exert great influence on model outputs of interest. Global sensitivity analysis (GSA) methods have been shown to be very effective for this purpose (Saltelli *et al.*, 2004). GSA methods use a design-of-experiment (DoE) approach to sample model parameters judiciously within the feasible parameter space with a limited number of model runs and employ various sensitivity measures to screen model parameters. There are numerous studies which use GSA methods to examine the parametric sensitivity of land surface models, NWP models, as well as climate models (Liu *et al.*, 2004; Bastidas *et al.*, 2006; Xiong *et al.*, 2010; Santanello *et al.*, 2011; Hou *et al.*, 2012; Johannesson *et al.*, 2014). Several studies have examined the parametric sensitivities of the WRF model with respect to different physical processes (Ruiz *et al.*, 2007; Loridan *et al.*, 2009; Kim and Wang, 2011; Yang *et al.*, 2012; Di *et al.*, 2015). Another key measure used in parameter estimation of NWP models is the use of surrogate models to emulate the response surface of NWP models to reduce the computational demand (O'Hagan *et al.*, 2006; Neelin *et al.*, 2010). Once the surrogate model is established, any follow-up parameter estimation studies can be carried out on the surrogate model instead of the original dynamical model (Wang *et al.*, 2014).

In our previous work, we have investigated the parameter sensitivities of the WRF model with respect to precipitation forecasting skill (Di *et al.*, 2015). Of 23 parameters examined, we found that less than ten of them are very sensitive in influencing precipitation forecasting. Since the WRF model involves more than just precipitation forecasting, other meteorological variables are also of great interest, such as surface air temperature and pressure, wind speed, humidity, and long-wave and short-wave radiation. In addition, it is very important to know how some atmospheric variables, such as total precipitable water in the atmosphere, boundary-layer height, cloud cover and the outgoing radiation at the top of the atmosphere, respond to different parameter specifications. In this article, the sensitivities of the WRF model parameters for those meteorological variables are analysed. The goal is to identify which model parameters exert the most influence on model outputs of different meteorological variables. The results will form the basis for multi-objective parameter optimization in the follow-up studies.

The article is organized as follows: section 2 describes the sensitivity analysis method used in this study. Section 3 presents the experimental design and the data. Section 4 discusses and analyses the experimental results. Section 5 provides summary and conclusions.

2. Methodology

The purpose of sensitivity analysis (SA) is to apportion the influence of different model inputs (i.e. parameters) on model outputs of interest. The SA process works as follows: (i) select the right model to be used and identify its tunable parameters, (ii) define the feasible ranges and distributions of the tunable parameters using prior knowledge, (iii) choose an appropriate SA method and objective functions to quantify the parameter sensitivity, (iv) conduct design of experiment (DoE) to sample the parameter space and run the model with those parameter samples, and (v) analyse the model outputs generated by different inputs and obtain the SA results.

For this study, we investigate the sensitivities of different WRF model outputs to the specification of its model parameters. The selection of the parameters and the feasible ranges and distributions of those parameters are presented in section 3.1. The Morris one-at-a-time (MOAT) is chosen as the SA method in this study for its efficiency (Morris, 1991). The specific MOAT steps are as follows: considering a model with m parameters, let $X=(x_1, x_2, x_3, \cdots, x_m)$ be the parameter vector, with the range of each parameter normalized to [0, 1] and divided into p equally spaced intervals. An initial parameter set, $X^0=(x_1^0, x_2^0, x_3^0, \cdots, x_m^0)$, is sampled in the feasible space, with each element of X^0 taking on a value randomly selected out of the set $\{0, 1/(p-1), 2/(p-1), \cdots, (p-2)/(p-1), 1\}$. Run the model with X^0 and then compute its objective function value $f(X^0)$. Then perturb a single parameter from X^0 (say x_j^0) by Δ_j to obtain $X^1=(x_1^0, x_2^0, x_3^0, \cdots, x_j^0+\Delta_j, \cdots, x_m^0)$ and then compute $f(X^1)$, where Δ_j is a pre-selected multiple of $1/(p-1)$ with a positive or a negative sign. Compute the gradient $d_j=\frac{f(X^1)-f(X^0)}{\Delta_j}$. Repeat this process for all $j \in \{1, 2, \ldots, m\}$ to complete a MOAT path and record $D^1=\{d_1, d_2, \ldots, d_m\}$. For robust results, r random replicates of several complete MOAT paths are required, i.e. $D=\{D^1, D^2, \ldots, D^r\}$.

There are two sensitivity indices for the MOAT method:

$$\mu_j=\sum_{i=1}^{r}|d_j(i)|/r, \tag{1}$$

$$\sigma_j=\sqrt{\sum_{i=1}^{r}(d_j(i)-\mu_j)^2/r}, \tag{2}$$

where μ_j, the average of absolute gradients associated with parameter j, represents the parameter's overall effect; σ_j, the standard deviation of the gradients associated with parameter

Table 1. Specific parametrization schemes used for the WRF model set-up.

Physical process	Specific scheme
Surface layer	MM5 Monin–Obukhov scheme (Dudhia *et al.*, 2005)
Cumulus	Kain–Fritsch Eta scheme (Kain, 2004)
Microphysics	WSM 6 single-class scheme (Hong and Lim, 2006)
Short-wave radiation	Dudhia scheme (Stephens *et al.*, 1984; Dudhia, 1989)
Long-wave radiation	RRTM scheme (Mlawer *et al.*, 1997)
Land surface	Noah land surface model scheme (Chen and Dudhia, 2001)
Planetary boundary layer	Yonsei University (YSU) scheme (Hong *et al.*, 2006)

j, describes the covariant effect of this parameter with other parameters, also known as the interactive effect. The larger the μ_j value, the more sensitive the parameter is. When σ_j is large, it means the combined effect of parameter *j* with other parameters on model outputs is not simply additive, but compensatory.

3. Numerical experimental design

3.1. WRF model set-up and selection of tunable parameters

Advanced Research WRF (ARW) version 3.3.1 was used to analyse the model parameter sensitivity. The WRF model represents seven different physical processes: microphysics, cumulus convection, near-surface physics, land-surface physics, planetary boundary-layer physics, and atmospheric long-wave and short-wave radiative transfer. For each physical process, there are numerous alternative parametrization schemes to choose from. In this study we choose a specific combination of parametrization schemes that is used by the Beijing Institute of Urban Meteorology (Table 1).

For the study area, we used a two-grid horizontally nested simulation area encompassing the Greater Beijing Area (Figure 1). For the outer layer (i.e. d01 area in Figure 1), the horizontal resolution was 27 km with a total of 88 points in the east–west direction and 56 points in the north–south direction. For the inner layer (i.e. d02 area in Figure 1), the horizontal resolution was 9 km, with a total of 61 points in the east–west direction and 49 points in the north–south direction. In the vertical direction, there are 38 layers partitioned based on the air pressure. The NCEP $1^\circ \times 1^\circ$ gridded reanalysis dataset provided the initial and lateral boundary conditions for the WRF model (http://rda.ucar.edu/datasets/ds083.2/index.html#!description). Note that we used the 3 km land use data in which there were 33 categories of land use to describe the underlying surface conditions (Zhang *et al.*, 2013). Since we are interested in the forecast of high intensity precipitation events over the summer, nine 5-day rainfall events from June, July and August between 2008 and 2010 were selected for the sensitivity analysis of model parameters (Figure 2).

Based on our prior knowledge, the reading of related literature and the communications with WRF experts and WRF parametrization scheme developers, we identified 23 parameters as important to forecasting of summer storms (Xiong *et al.*, 2010; Hou *et al.*, 2012; Yang *et al.*, 2012; Li *et al.*, 2013). This list of parameters and their variation ranges are shown in Table 2. We must note that this list does not include all possible important parameters. However, the methodology we presented here can be generalized in other NWP model parameter sensitivity analyses.

3.2. Sensitivity analysis toolbox used

The Uncertainty Quantification Python Laboratory (UQ-PyL) software platform developed at Beijing Normal University was used for the sensitivity analysis. UQ-PyL is an uncertainty analysis and optimization tool for highly complex dynamic system models (Wang *et al.*, 2016). It provides a large number of functions, including experimental design, sensitivity analysis, statistical analysis, surrogate modelling, and numerical optimization. In

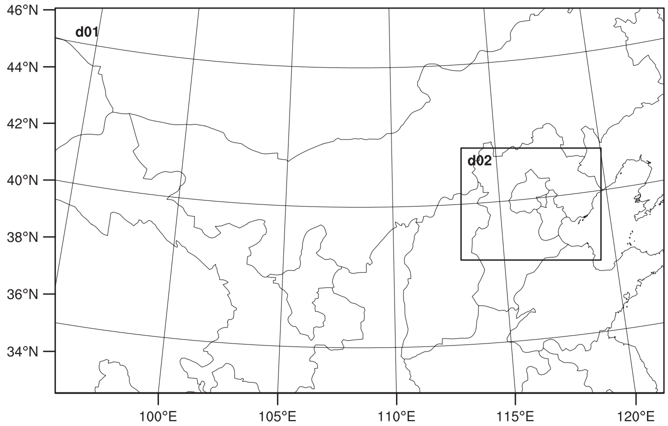

Figure 1. Two layers nested simulation area. The horizontal resolution of the outer layer is 27 km and there are in total 88 points in the west–east direction and 56 points in the south–north direction. The horizontal resolution of the inner layer (d02) is 9 km and there are in total 61 points in the west–east direction and 49 points in the north–south direction.

this study, we used the MOAT method from UQ-PyL for the SA study.

Based on our previous studies, the MOAT method requires about ten replications to obtain reliable SA results (Li *et al.*, 2013; Gan *et al.*, 2014; Di *et al.*, 2015). Therefore, for this study, we generated the MOAT design with ten replications of random MOAT paths (i.e. $r = 10$). Since 23 parameters are considered, a total of $(23 + 1) \times 10 = 240$ parameter samples were generated for the SA study based on the MOAT design. In terms of algorithmic parameters, the MOAT method used four levels to sample model parameters (i.e. $p = 4$), and the perturbation for parameter *j* is set to $\Delta_j = 2/p$, where $j = 1, 2, \ldots, m$ and *m* is the parameter dimension.

3.3. The WRF model outputs and the cost function used for the SA study

We conducted SA study of WRF model outputs to different model parameter values for many meteorological variables, including precipitation (PR), surface air temperature (SAT), wind speed (WS), surface atmospheric pressure (SAP), relative humidity (RH), downward short-wave radiative flux (DSWRF) and long-wave radiative flux (DLWRF). We also examined the parameter sensitivities of atmospheric variables such as cloud fraction (CF) and planetary boundary-layer height (PBLH), total precipitable water (TPW) and outgoing long-wave radiation flux at the top of the atmosphere (OLR). The sensitivities are evaluated based on the discrepancies of model simulations using different parameter values and the model simulations using the default parameter values (i.e. the simulations from a control run).

The discrepancy between the model simulation and the reference target (i.e. observation or control simulation) is also known as the cost function or the objective function. There are many different types of objective functions. One commonly used objective function is the root-mean-squared error (RMSE) or the mean absolute error (MAE); both represent the aggregate difference between model simulation and reference target. In operational forecasting, there are many other cost functions or performance metrics such as Bias Score, Threat Score, Equitable Threat Score, and Proportion of Correct Forecast, among others.

In this study, RMSE was used as the cost function for all variables. The RMSE is calculated as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(S_i\text{-}T_i)^2}, \tag{3}$$

where S_i represents the 3-hourly simulations at point *i* (time or space) and T_i represents simulation targets at point *i*, which can

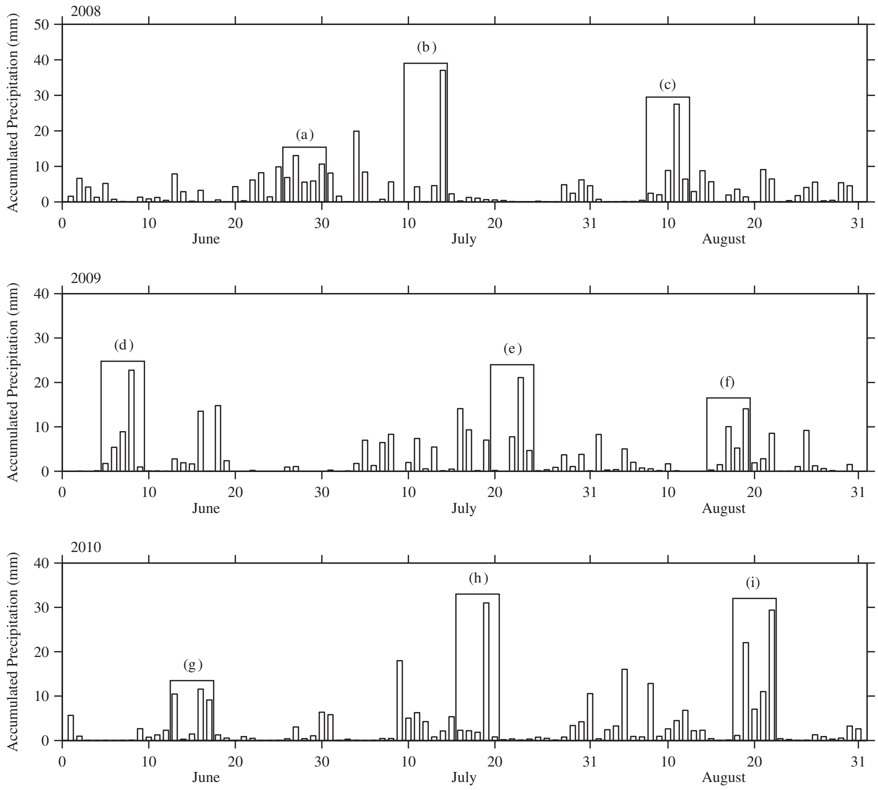

Figure 2. Daily regional average of rainfall in the D02 area. Black boxes are used to mark the events that will be simulated. For (a), the simulation date is from 26 to 30 June 2008. For (b), the simulation date is from 10 to 14 July 2008. For (c), the simulation date is from 7 to 11 August 2008. For (d), the simulation date is from 5 to 9 June 2009. For (e), the simulation date is from 20 to 24 July 2009. For (f), the simulation date is from 14 to 18 August 2009. For (g), the simulation date is from 13 to 17 June 2010. For (h), the simulation date is from 16 to 20 July 2010. For (i), the simulation date is from 17 to 21 August 2010.

Table 2. List of tunable parameters for the WRF model.

Index	Scheme	Parameter	Default	Range	Description
P1	Surface layer (module_sf_sfclay.F)	xka	2.4e−5	[1.2e−5 5e−5]	The parameter for heat/moisture exchange coefficient ($s\,m^{-2}$)
P2		czo	0.0185	[0.01 0.037]	The coefficient for converting wind speed to roughness length over water
P3	Cumulus (module_cu_kfeta.F)	pd	1	[0.5 2]	The multiplier for downdraught mass flux rate
P4		pe	1	[0.5 2]	The multiplier for entrainment mass flux rate
P5		ph	150	[50 350]	Starting height of downdraught above USL (hPa)
P6		timec	2 700	[1 800 3 600]	Average consumption time of CAPE(s)
P7		tkemax	5	[3 12]	The maximum turbulent kinetic energy (TKE) value in sub-cloud layer ($m^2\,s^{-2}$)
P8	Microphysics (module_mp_wsm6.F)	ice_stokes_fac	14 900	[8 000 30 000]	Scaling factor applied to ice fall velocity (s^{-1})
P9		n0r	8e+6	[5e+6 1.2e+7]	Intercept parameter of rain (m^{-4})
P10		dimax	5e−4	[3e−4 8e−4]	The limited maximum value for the cloud-ice diameter(m)
P11		peaut	0.55	[0.35 0.85]	Collection efficiency from cloud to rain auto conversion
P12	Short-wave radiation (module_ra_sw.F)	cssca	1e−5	[5e−6 2e−5]	Scattering tuning parameter ($m^2\,kg^{-1}$)
P13		Beta_p	0.4	[0.2 0.8]	Aerosol scattering tuning parameter ($m^2\,kg^{-1}$)
P14	Long-wave (module_ra_rrtm.F)	Secang	1.66	[1.55 1.75]	Diffusivity angle for cloud optical depth computation
P15	Land surface (module_sf_noahlsm.F)	hksati	1	[0.5 2]	The multiplier for hydraulic conductivity at saturation
P16		porsl	1	[0.5 2]	The multiplier for the saturated soil water content
P17		phi0	1	[0.5 2]	The multiplier for minimum soil suction
P18		bsw	1	[0.5 2]	The multiplier for Clapp and Hornbereger 'b' parameter
P19	Planetary boundary layer (module_bl_ysu.F)	Brcr_sbrob	0.3	[0.15 0.6]	Critical Richardson number for boundary layer of water
P20		Brcr_sb	0.25	[0.125 0.5]	Critical Richardson number for boundary layer of land
P21		pfac	2	[1 3]	Profile shape exponent for calculating the momentum diffusivity coefficient
P22		bfac	6.8	[3.4 13.6]	Coefficient for Prandtl number at the top of the surface layer
P23		sm	15.9	[12 20]	Countergradient proportional coefficient of non-local flux of momentum

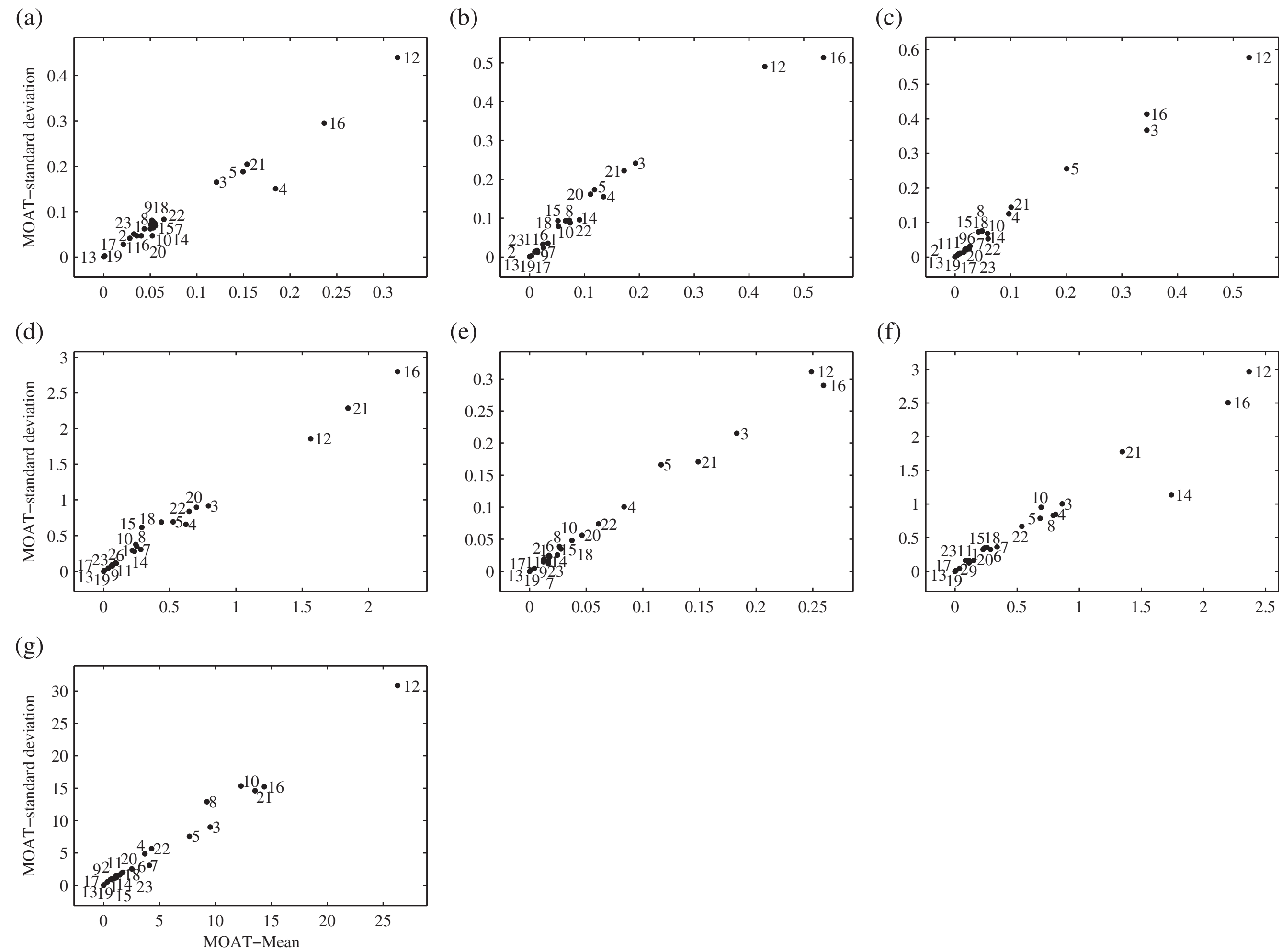

Figure 3. The MOAT parameter sensitivity plots for conventional observational variables. (a) PR, (b) SAT, (c) SAP, (d) RH, (e) WS, (f) DLWRF, and (g) DSWRF.

be the corresponding observations or the simulations of a control run. In this study, *RMSE* is computed using the simulations from a control run that uses default model parameters as the targets.

4. Results and analysis

4.1. Parameter sensitivity of different meteorological variables simulated by the WRF model

The WRF model was run 240 times using the parameter samples generated according to the MOAT design described in section 3.2. We evaluated the *RMSE* values of the simulations for different meteorological variables from the 240 model runs and computed the MOAT sensitivity indices according to Eqs (1) and (2).

Figure 3 shows the MOAT SA results for the surface meteorological variables. For each subplot, the horizontal axis and the vertical axis represent the values of the MOAT mean and MOAT standard deviation, respectively. In those plots, the larger the value of the MOAT mean is, the more sensitive the parameter is. Meanwhile a large value for the MOAT standard deviation indicates high interaction of the parameter with other parameters. Parameters P12, P16, P21, P3 and P5 appear as very sensitive parameters, while parameters P13, P19 and P17 are not sensitive parameters for all of those variables considered. P4 is considered one of the sensitive parameters for all of the variables except for DSWRF. P8 and P10 appear as the most sensitive parameters for DSWRF and DLWRF. P14 is one of the most sensitive parameters for DLWRF. P20 and P22 are among the most sensitive parameters for RH.

The parameter sensitivities for atmospheric variables such as CF, PBLH, OLR and TPW were also evaluated. Figure 4 shows the MOAT SA results for those variables. The results show that P12, P16 and P21 rank at or near the top of the most sensitive parameters for all four variables and P13, P19 and P17 are the least sensitive. In addition, P8 and P10, the two microphysics-related parameters, are the most sensitive parameters for CF. They also exert great influence on OLR. P4 is considered very sensitive for TPW, and P22 and P20 are among the most sensitive for PBLH.

We normalized the MOAT mean values of all meteorological variables to [0 1] and plot them in Figure 5. The vertical axis denotes the normalized MOAT means and the horizontal axis denotes the different parameters. The darkest colour corresponds to 1 (i.e. the most sensitive), while blank colour denotes 0 (i.e. the least sensitive). From the figure, it can be observed that P12, P16 and P21 are the most sensitive parameters for all of the variables. P3, P4 and P5 appear as very sensitive parameters for many of the variables, except one or two variables. It is apparent that P8 and P10 are the most sensitive parameters for CF and OLR. They also show significant sensitivity for DSWRF and DLWRF. Some parameters are only sensitive with respect to a few meteorological variables (e.g. P14 for DLWRF, and P20 and P22 for RH and PBLH). Twelve of the considered parameters are not sensitive to any variables (i.e. P1, P2, P6, P7, P9, P11, P13, P15, P17, P18, P19 and P23).

4.2. Effect of different model parameters on the errors of PR and SAT forecasts

The MOAT SA results presented above inform us which WRF model parameters exert the most influence on different meteorological variables. They can be used as a basis for parameter optimization of the WRF model to improve its forecasts of meteorological variables of interest such as PR and SAT. Conducting a proper parameter optimization study for the WRF

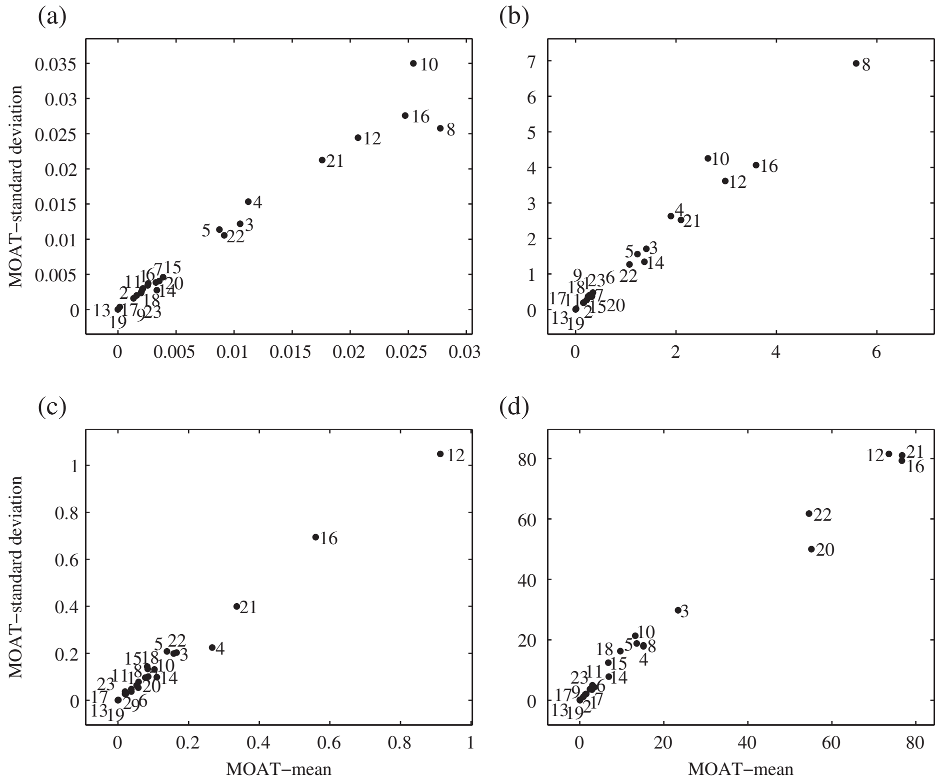

Figure 4. The MOAT parameter sensitivity plots for nonconventional observational variables. (a) CF, (b) OLR, (c) TPW, and (d) PBLH.

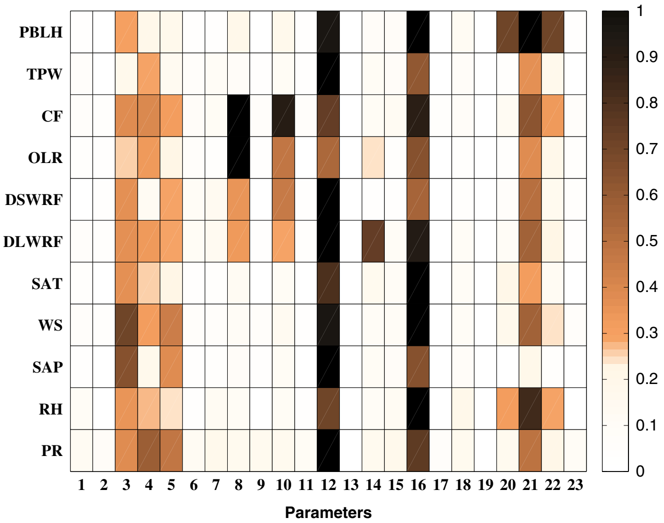

Figure 5. The normalized MOAT means of different parameters for meteorological variables considered, with 1 implying the most sensitive and 0 the least sensitive parameter.

Table 3. Root-mean-square error (RMSE) of PR and SAT simulations using default and optimized parameter sets.

Name	Default	Optimized	Improvement (%)
PR	3.332	2.584	22.45
SAT	2.504	2.206	11.90

model is, however, an enormous task that exceeds the scope of this article. Still, we can use the simulation results from the SA study to gain insight into how forecast errors of variables such as PR and SAT can be reduced by using a different model parameter set from the default one. To do this, we computed the RMSE values of PR and SAT simulations for all 240 parameter samples obtained from the SA study and selected the parameter sets corresponding to the lowest RMSE values for PR and SAT, respectively. Those values are then compared to the RMSE values for PR and SAT simulations using the default model parameter set (Table 3). It is clear that the RMSE values can be improved by at least 22 and 11% for PR and SAT, respectively, when model parameters are changed from the default parameters. Figures 6 and 7 show the observed and two sets of forecasted daily average PR and SAT values of all nine storm events over the forecast domain. Also shown in those figures are the spatial patterns of the residuals between observed and forecasted daily averages for PR and SAT. Those results confirmed the improvement in PR and SAT simulations. The spatial patterns of the daily average of the PR and SAT simulations generated using the parameters corresponding to the lowest RMSE are much closer to the observed patterns compared to that using the default parameters (Figures 6(b,c) and 7(b,c). The residuals between observed and forecasted daily averages for PR and SAT are also reduced dramatically. Note that the improvement is achieved with model parameters sampled using the MOAT design at very coarse grids. If more powerful optimization methods are used, more improvement can be achieved.

4.3. *Discussion of the SA results of all meteorological variables*

It is reasonable that parameter P12, P16 and P21 are the most sensitive for all of the variables. For P12 (scattering tuning parameter in the clear sky), it directly affects the solar radiation reaching to the ground (DSWRF). With a larger P12, DSWRF will decrease, leading to less evaporation and lower land-surface heating rate, so surface atmospheric temperature (SAT) will be lower, specific humidity and total precipitable water (TPW) will go down. For P16 (the multiplier for the saturated soil water content), this parameter affects the saturated soil water content. Because saturated soil water content is an important factor for heat and moisture transportation in the soil, it will affect the evaporation and heat exchange between the land and atmosphere. Consequently, this parameter affects the surface atmospheric temperature (SAT), specific humidity and total precipitable water (TPW). For P21 (profile shape exponent for calculating the turbulent momentum diffusivity coefficient), this parameter affects the intensity of turbulence by controlling the

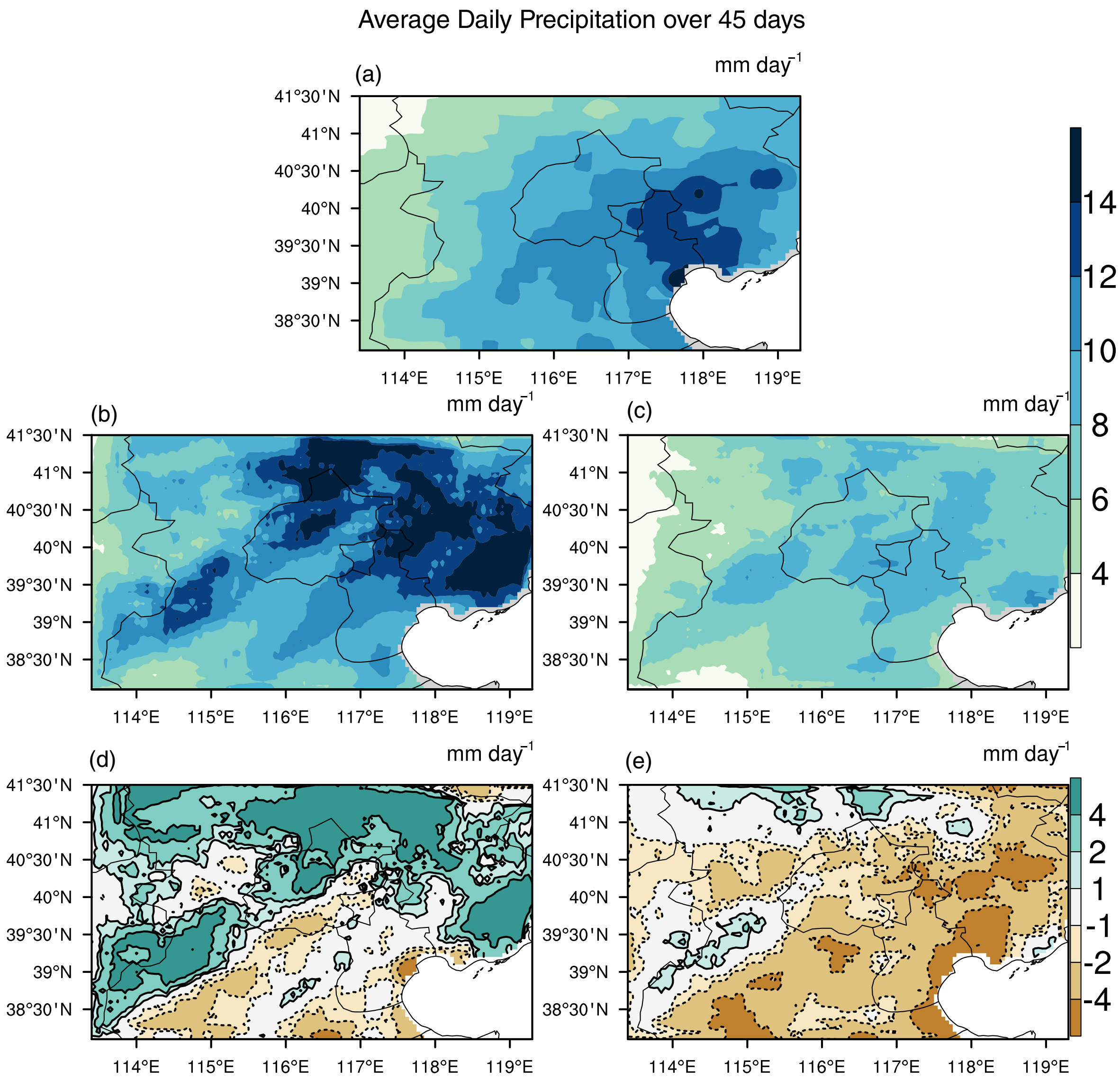

Figure 6. Comparison of daily average simulated precipitation (PR) for the nine 5-day events using default and optimized parameters. In (d) and (e), solid and dotted contour lines represent positive and negative, respectively. (a) Obs, (b) Default, (c) Opt, (d) Default−Obs, and (e) Opt−Obs.

turbulent momentum diffusivity coefficient in the PBL, so the wind speed (WS) and planetary boundary-layer height (PBLH) will be affected. Because momentum exchange coefficient is one determining factor for the exchange coefficients for heat and moisture, this parameter also affects the upward transportation of heat and moisture near the surface. As a result, the surface temperature (SAT) and specific humidity will also be influenced by this parameter.

The sensitivity of P12, P16 and P21 on other meteorological variables can be explained based on their effect on surface temperature (SAT) and specific humidity. As the SAT and specific humidity are changed, the relative humidity (RH) and surface atmospheric pressure (SAP) will also be changed. Because SAT influences the strength of turbulence, the change of SAT will lead to the change of the planetary boundary-layer height (PBLH). Due to the different heat capacity of different land use types, the change of SAT is not uniform in space, so the change of SAP is not uniform, and then the wind speed (WS) will be affected. SAT and specific humidity also affect the stability of the atmosphere, and then affect the convection. With larger SAT and specific humidity, the triggering of convection is easier, leading to more precipitation (PR) and cloud cover (CF). Because of the radiation effect of cloud, downward short-wave radiation (DSWRF), downward long-wave radiation (DLWRF) and outgoing long-wave radiation (OLR) will be changed.

The other three sensitive parameters for many of the variables, except one or two, are P3, P4 and P5. Their sensitivity also can be interpreted by physics. For parameter P3 (the multiplier for downdraught mass flux rate), P4 (the multiplier for entrainment mass flux rate) and P5 (starting height of downdraught above updraught source layer (USL)), they all control the intensity of convection. The perturbation of these parameters will change the intensity of convection, and then the formation of cloud (cloud fraction (CF), cloud height, etc.), the occurrence of precipitation and precipitation amount (PR). Variables related to cloud such as outgoing long-wave radiation (OLR), downward short-wave radiation flux (DSWRF), and downward long-wave radiation flux (DLWRF) will also be affected. With the occurrence of precipitation, the surface atmospheric temperature (SAT) will be lower and relative humidity (RH) will increase, so the surface atmospheric pressure (SAP) will also change. When the precipitation decreases, total precipitable water (TPW) will increase. Because the convection will affect the atmospheric circulation, these parameters are also sensitive to wind speed (WS).

Another noticeable result is that parameter P8 and P10 appear to be very sensitive for CF, OLR, DSWRF and DLWRF. P8 (scaling factor applied to ice fall velocity) and P10 (the limited maximum value for the cloud-ice diameter) both modulate the terminal velocities of falling ice crystals in the microphysics scheme. Any change of their value will significantly influence the attributes of cloud (e.g. cloud water and cloud ice) by controlling the sedimentation of ice crystals. Because the cloud fraction (CF) in WRF is estimated based on the cloud attributes (cloud water,

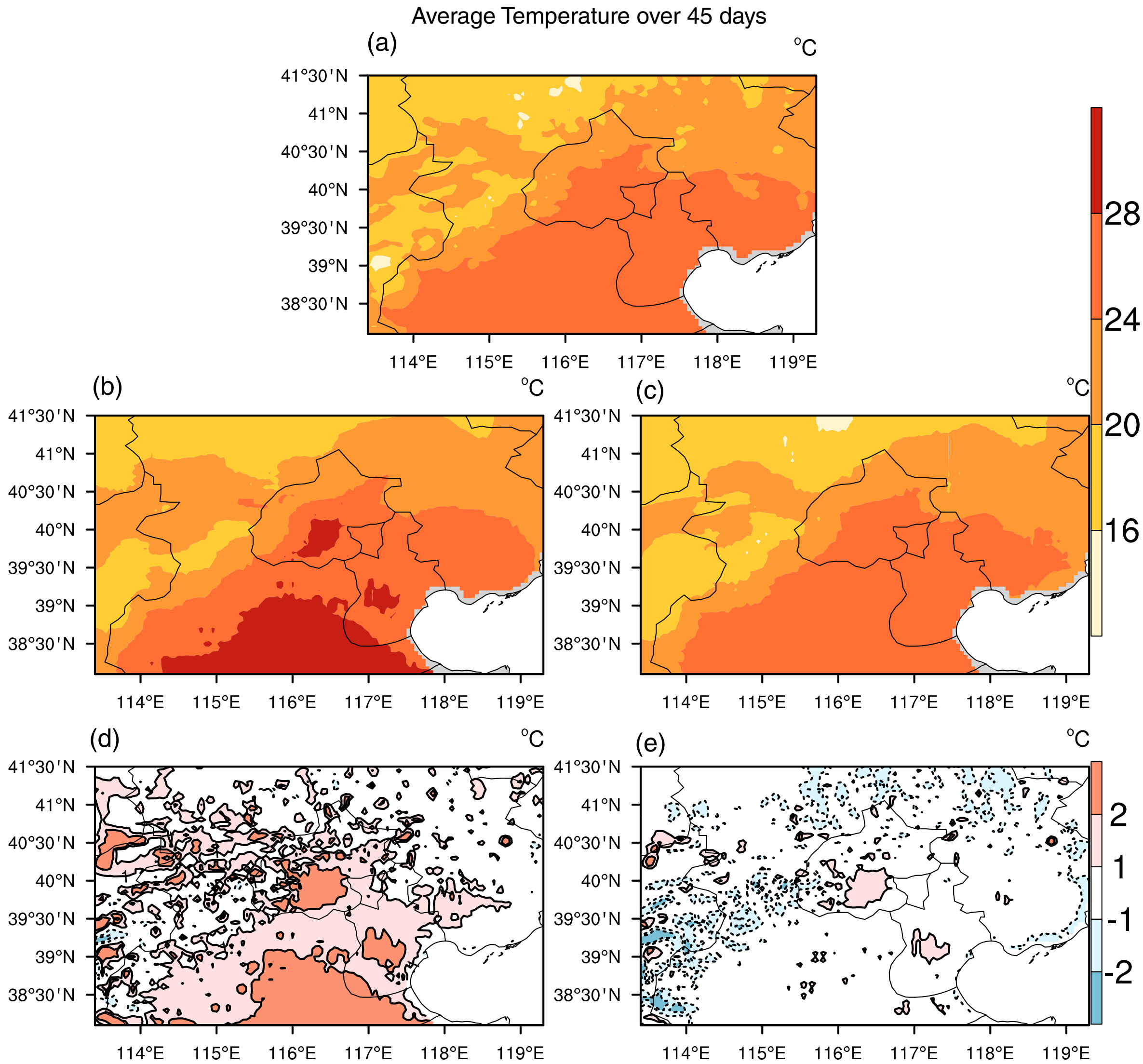

Figure 7. Comparison of daily average simulated surface air temperature (SAT) at 2 m for the nine 5-day events using default and optimized parameters. In (d) and (e), solid and dotted contour lines represent positive and negative, respectively. (a) Obs, (b) Default, (c) Opt, (d) Default−Obs, and (e) Opt−Obs.

ice and snow) (Zheng, 2013), CF will be affected. Since cloud efficiently affects the amount of DSWRF by reflecting the solar radiation, and the amount of DLWRF and OLR by absorbing and emitting long-wave radiation, parameters P8 and P10 are sensitive for DSWRF, DLWRF and OLR.

The SA results from this study are all obtained for rainy events as our original motivation was to improve forecasting of summer monsoon storms in the Greater Beijing Area. It is not certain that the results for wet events remain valid for dry events. To answer this question, we performed the SA analysis for three dry events. We found that the sensitivity of some parameters remain the same during both the wet and dry events. But some parameters that are sensitive for wet events become non-sensitive for dry events. For example, P16, the soil porosity parameter, is one of the most sensitive parameters for rainy events, but it is totally non-sensitive for the dry events. This is because soil porosity does not affect thermal and water exchange during dry periods. There are similar reversals in the sensitivities of parameters P3, P4 and P5, as those parameters are related to the convection process. During the dry events, convection is not active and, thus, those parameters show no impact on the meteorological variables we considered.

5. Conclusions

In this study, we identified the most sensitive parameters of the WRF model for 11 variables. Twenty-three tunable parameters from seven fixed physical process parametrization schemes were considered. Their sensitivities were evaluated based on forecast errors that were calculated over nine 5-day forecasts during the summer monsoon from 2008 to 2010 in the Greater Beijing Area in north China. Based on the MOAT global sensitivity analysis method, 240 sets of parameters were generated to estimate the sensitivity of the parameters.

We found that certain parameters are very sensitive with respect to all of the meteorological variables considered, while 12 out of 23 adjustable parameters are shown to be not sensitive at all to any of the meteorological variables. This result is very significant as it tells us that if we would like to tune some of the adjustable parameters, we need to focus on only a few of them, not all.

We would like to caution readers that parameter sensitivity is generally dependent on local conditions. Our results are obtained for rainy events. We found some sensitive parameters become insensitive for dry events. Therefore, the SA results from this study may not be directly indicative of other conditions or other areas. If the study condition or area is changed, it is preferable to re-evaluate the sensitivity of the adjustable parameters using the strategy presented in this study or other similar strategy.

We would like to emphasize that the 23 parameters considered here are not all of the tunable parameters in the WRF model. However, the results obtained still can provide a strong reference for anyone who would like to try a similar strategy. Furthermore, the results of this study form a strong basis for our further research on optimization of the most sensitive parameters.

Acknowledgements

This research is partially supported by the National Natural Sciences Foundation of China (No. 41375139), the Ministry of Science and Technology of the People's Republic of China National Science and Technology 973 Program (Grant No. 2015CB452805 and No. 2015DFA20870), and the Beijing Municipal Science and Technology Commission (No. Z141100003614052 and No. Z151100002115045). We would like to thank S.Y. Hong of Yonsei University, S. Miao, S. Fan and Y. Zhang of the China Meteorological Administration for their expert knowledge and advice.

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