Parameter Estimation Using the Genetic Algorithm in Terms of Quantitative Precipitation Forecast

Yong Hee Lee, Seon Ki Park, Dong-Eon Chang, Jong-Chul Ha and Hee-Sang Lee

Abstract In this study, the optimal parameter estimation is performed for both physical and computational parameters in a mesoscale meteorological model, and its impact on the quantitative precipitation forecasting (QPF) is assessed for a heavy rainfall case occurred at the Korean peninsula in June 2005. Experiments are carried out using the PSU/NCAR MM5 model and the genetic algorithm (GA) for two parameters: the reduction rate of the convective available potential energy in the Kain-Fritsch (KF) scheme for cumulus parameterization, and the Asselin filter parameter for numerical stability. The fitness function is defined based on a QPF skill score. It turns out that each optimized parameter significantly improves the QPF skill. Such improvement is maximized when two optimized parameters are used simultaneously. Our results indicate that optimizations of computational parameters as well as physical parameters and their adequate applications are essential in improving model performance.

1 Introduction

Numerical weather/climate prediction models contain numerous parameterizations for physical processes and numerical stability. Parameterizations are based on physical laws but typically contain parameters whose values are not known precisely. The values of the parameters directly or indirectly affect the performance of model, and thus uncertainties in parameter values may lead to sensitive results from some models, especially with high resolution and sophisticated microphysics (e.g., Park and Droegemeier, 1999). Accordingly, optimal estimation of parameters is one of several essential factors in improving the accuracy of numerical forecasts.

Recently, efforts have been made to obtain better estimation of parameters for numerical forecast models using various methods such as the variational technique using a full-physics adjoint model (Zhu and Navon, 1999), the Bayesian stochastic

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inversion (BSI) based on multiple very fast simulated annealing (VFSA) (Jackson et al., 2004), the downhill simplex method (Severijns and Hazeleger, 2005), and the ensemble Kalman filter (EnKF) (Aksoy et al., 2006).

The genetic algorithm (GA), which is a global optimization technique, has also been applied to some optimization problems including parameter estimation, especially for simple models. Compared to traditional optimization methods based on the gradient of a function, the GA is more appropriate when the function includes some complexities and/or discontinuities (Barth, 1992). Major advantages of the GA include that: (1) derivatives of fit function with respect to model parameters are not required; and (2) nonlinearity between the model and its parameters can be handled (Holland, 1975; Goldburg, 1989; Charbonneau, 2002).

Based on the optimization of model parameters such as the biharmonic horizontal diffusion coefficient, the ratio of the transfer coefficient of moisture to the transfer coefficient of sensible heat, and the Asselin filter coefficient, Zhu and Navon (1999) demonstrated that the positive impact of the optimally-estimated parameter values persists for longer than that of the optimized initial conditions. The parameter estimation problems have been explored to a wide scope including the land surface parameters (Jackson et al., 2004), the radiation and cloud parameters (Severijns and Hazeleger, 2005), the vertical eddy mixing coefficient (Aksoy et al., 2006), and even for the purpose of experiment design (Barth, 1992, Hernandez et al., 1995). However, attempt has seldom been made on the parameter estimation problem associated with the quantitative precipitation forecasting (QPF).

This study focuses on optimal parameter estimation to improve the QPF skill in a mesoscale meteorological model using the GA. Section 2 describes characteristics of the model and parameters, and Sect. 3 explains the details of GA for parameter estimation. Discussions on results appear in Sect. 4, and conclusions are provided in Sect. 5.

2 Case, Model and Experiments

A heavy rainfall case in Korea is selected for experiments. It occurred in the west-central part of the Korean peninsula, associated with a summer monsoon front, with a local maximum 6-hr accumulated rainfall of 100 mm in Seoul from 1200 UTC to 1800 UTC 26 June 2005.

In this study, the 5th-generation Pennsylvania State University-National Center for Atmospheric Research Mesoscale Model (MM5) version 3.6.3 (Grell et al., 1994) is employed. The computational domain consists of 218×181 grids in the horizontal, with a resolution $\Delta x = \Delta y = 18$ km, and 35 layers in the vertical. The model domain is shown in Fig. 1a along with terrain. The MM5 is integrated up to 12 hrs starting from 0600 UTC 26 June 2005, with a time step $\Delta t = 45$ s. Schemes for physical processes include: the MRF PBL (Hong and Pan, 1996), the Kain-Fritsch (KF) cumulus parameterization (Kain, 2003), the Dudhia radiation (Dudhia, 1989)

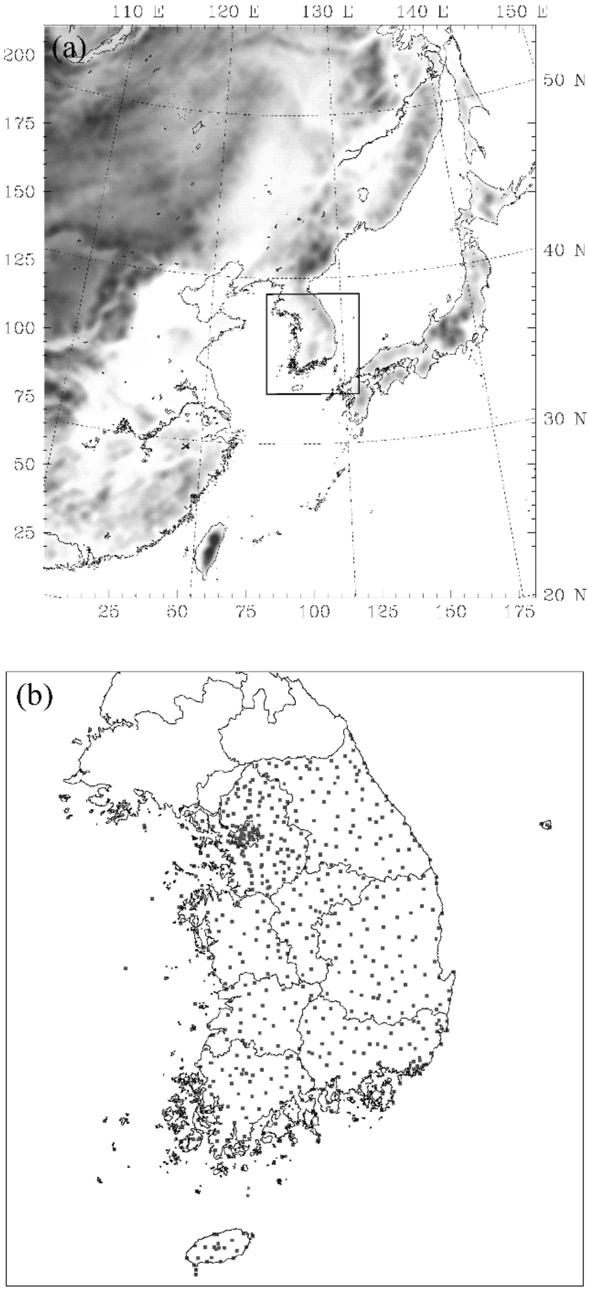

Fig. 1 (**a**) Domain configuration of MM5 along with topography. The inner box indicates the verification area. (**b**) The location of the 592 rain gauge stations in Korea used for the QPF verification. The average distance of rain gauge stations is about 18 km

and RRTM, the Schultz microphysics (Schultz, 1995), and the five-layer soil scheme (Dudhia, 1996).

For the parameter estimation study, we focus on the closure assumption of the KF parameterization and the Asselin filter coefficient in MM5. The "closure" in the KF parameterization relates the intensity of convective activity to the resolved-scale properties in a model, and the assumes that convection consumes at least 90% of the environmental convective available potential energy (CAPE) over an advective time period, bounded by a maximum of 1 hr and a minimum of 30 min (Kain, 2003). However, Saito et al. (2006) found that this setting tended to over stabilize the model atmosphere, making strong rainfall decrease with time in the forecast period of 18 hours. To prevent this undesirable excessive stabilization of the model atmosphere, the reduction rate of CAPE in the column, for a single application of the KF scheme, is diminished from the default value to 85%. In this study, an optimal parameter estimation experiment will be carried out to obtain the optimal value of the "closure assumption" in the KF scheme.

The temporal differencing in MM5 consists of leapfrog steps with an Asselin filter (Asselin, 1972). Splitting of the solution often associated with the leapfrog scheme is avoided by using this filter. It is applied to all variables α as

$$\hat{\alpha}^t = (1-2\nu)\alpha^t + \nu(\alpha^{t+1} + \hat{\alpha}^{t-1}), \tag{1}$$

where $\hat{\alpha}$ is the filtered variables, and $\nu \in [0,1]$ is the Asselin filter parameter. The value of ν is set to 0.1 in MM5 for all variables (Grell et al., 1994). However, Bryan and Fritsch (2000) found that the Asselin filter parameter used in MM5 is a source of the unphysical thermodynamic structures. Another parameter estimation experiment in this study will be focused to obtain the optimal value of the Asselin coefficient. The lower bound of the Asselin coefficient is set to 0.01, while its upper bound is set to 0.3.

3 Methodology of Parameter Estimation

This study aims at performing optimal estimations of two parameters in MM5 using the GA. The GA is a global optimization approach based on the Darwinian principles of natural selection. This method, developed from the concept of Holland (1975), aims to efficiently seek the extrema of complex function – see Goldberg (1989) for a detailed description. Deb (2000) discussed an efficient constraint handling for the GA.

A key concept in the GA is the chromosome. A chromosome contains a group of numbers that completely specifies a candidate during the optimization process. Typically, the GA uses crossover, mutation, and reproduction to provide structure to a random search. The GA restricted to mere reproduction and mutation is a version of stochastic random search. The incorporation of the crossover operator, which mates two chromosomes, provides a qualitatively different search, one that has no counterpart in stochastic grammars. Crossover works by finding, rewarding and recombining "good" segments of chromosomes, and the more faithfully the segments of the chromosomes represent the better we can expect genetic algorithms to perform. The GA also uses randomization heavily in choosing a chromosome that will propagate to future generations. In general, the average fitness of individuals increases with each generation, through the process of natural selection. In each successive generation, individuals with bad genes are weeded out while those with good genes propagate their genetic code. The genetic code that determines the fitness of an individual is termed, logically enough, the chromosome of that individual. Given a chromosome, the GA should be able to ascertain its fitness. The performance and search time depend on the number of bits, the size of a population, the mutation and crossover rates, choice of features and mapping from chromosomes to the parameter itself, the inherent difficulty of the problem and possibly parameters associated with other heuristics.

For the parameter estimation experiments in this study, a GA package called the PIKAIA (Charbonneau, 2002) is employed. Each generation has 20 chromosomes. The crossover probability is set to 0.85, implying that 85% of the chromosomes in a generation are allowed to crossover in an average sense. The maximum and minimum mutation probability is set to 0.05 and 0.005, respectively.

Internally, the PIKAIA seeks to maximize a function $f(\mathrm{X})$ in a bounded n-dimensional space,

$$\mathrm{X} \equiv (x_1, x_2, \cdots, x_n), \qquad x_k \in [0.0, 1.0]\,\forall k \tag{2}$$

In our problem, there exist two adjustable parameters, i.e., $n = 2$. Then we may associate the reduction assumption of the KF scheme ε with x_1 and the Asselin filter parameter ν with x_2. The ranges of parameters are $0 \leq \varepsilon(x_1) \leq 0.95$ and $0.01 \leq \nu(x_2) \leq 0.3$, respectively.

The function to be optimized (i.e., Fitness) is defined by using a QPF skill score, the equitable treat score (ETS) (Schaefer, 1990),

$$\text{Fitness} = \sum_i ETS_i, \quad i = 1, 2, \cdots, 100 \tag{3}$$

where i is the precipitation threshold in mm. Here, the ETS is defined as:

$$ETS = \frac{H - R}{F + O - H - R}, \tag{4}$$

where H is the number of hits, and F and O are the numbers of samples in which the precipitation amounts are greater than the specified threshold in forecast and observation, respectively, and R is the expected number of hits in a random forecast $-R = FO/N$, where N is total number of points being verified.

Each generation includes 20 individual MM5 runs as a function of ε and ν. Every individual run with the two parameters is encoded by chromosomes and returns the accumulated rainfall to determine the fitness; thus the fitness function is dynamically coupled to the MM5 model. In each generation, the two parameters make independent search for the optimal solution concurrently; hence there exists no feedback between the two parameters.

Clearly, the relationship between the fitness function and the model parameters is strongly nonlinear. Therefore any other robust estimator can be substituted with little or no changes to the overall procedure of GA. Under the right conditions the GA has shown to converge to good solutions remarkably quickly and has the advantage that the rate of convergence varies in accordance with the complexity of the search space (Goldberg, 1989; Holland, 1975).

4 Results

In this study, two parameters in MM5 are optimized (i.e., the closure assumption of KF scheme, ε, and the Asselin filter coefficient, ν) to improve the QPF skill using the GA. Figure 2 depicts performance of chromosomes in terms of generations. In the first few generations, the performance of chromosomes improves significantly as the GA discovers and populates the best regions in the search space. The zeroth generation consisted of 20 chromosomes chosen randomly. The spread of fitness at the zeroth generation is quite large. This implies that both parameters (i.e., ε and ν) exert sensitive impact on the precipitation forecasts because the fitness function is defined in terms of a QPF skill score. The performance of average chromosomes

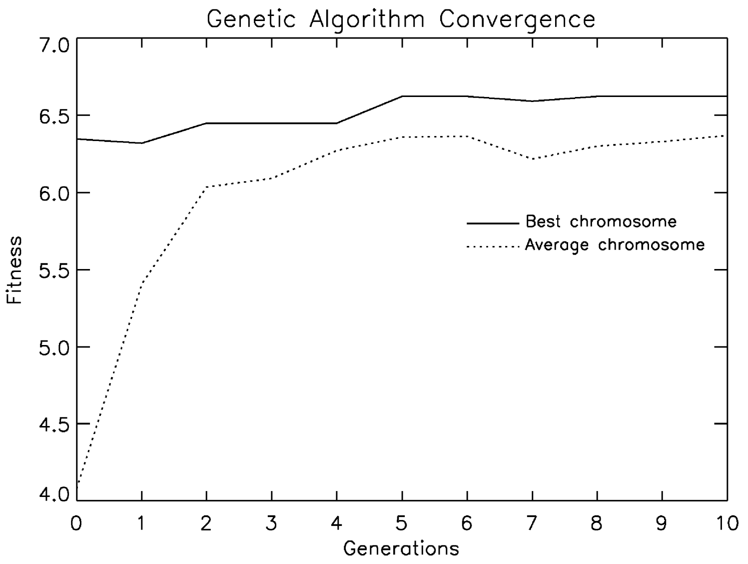

Fig. 2 Performance of the best chromosome in each generation and of an average chromosome in a generation. A typical GA does its tuning in stages called generations. The final solution has $(\varepsilon, \nu) = (0.01, 0.25)$

improved exponentially, up to the second generation (i.e., 60 runs MM5), as the GA discovers and populates the best regions in the search space. This implies that evolution for only a few generations is sufficient to obtain optimal estimation parameters. The final solutions of the two parameters are $\varepsilon = 0.0111781 \approx 0.01$ and $\nu = 0.2498580 \approx 0.25$, through global optimization in the fitness space which has multiple minima (not shown).

Figure 3 compares the ETSs computed for the 6-hr accumulated rainfall at forecast period of 6–12 hr from the following four experiments using: (1) the default parameter (CNTL; $\varepsilon = 0.9$, $\nu = 0.1$); (2) no convective parameterization scheme (NC; ε =none, $\nu = 0.1$); (3) the revised KF parameter (KF; $\varepsilon = 0.01$, $\nu = 0.1$); (4) the revised Asselin filter parameter (AF; $\varepsilon = 0.9$, $\nu = 0.25$); and (5) the revised parameters for both the KF scheme and the Asselin filter (KF-AF; $\varepsilon = 0.01$, $\nu = 0.25$). The ETSs of the default run dropped rapidly with increasing threshold values reaching lower than 0.1 at thresholds larger than 30 mm. In general, it can be noticed that the GA-estimated parameters give positive effect on increasing the QPF skill, either independently or together.

In the original KF scheme, ε is set to 0.9; that is, the convection consumes the pre-existing CAPE by 90%. However, the GA-estimated value (i.e., $\varepsilon = 0.01$) is quite different from the original. This implies that the convective rainfall in the selected case requires almost no consumption of the pre-existing CAPE. It is notified that, compared with convective systems in the North America, those in the East

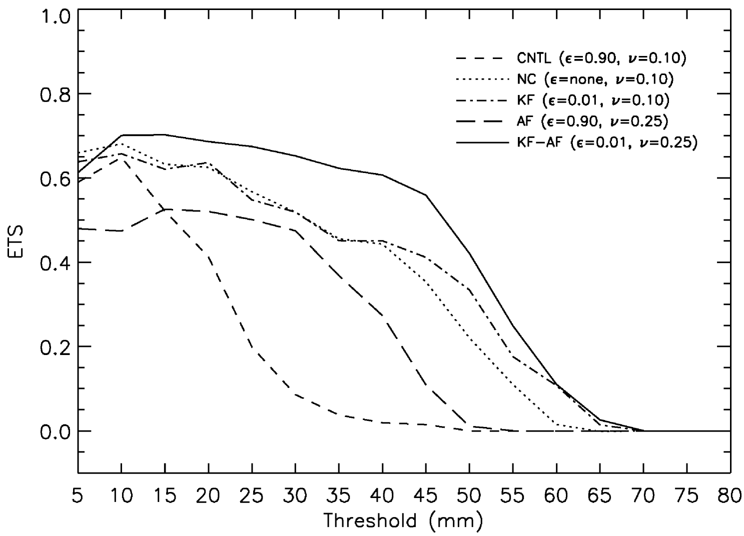

Fig. 3 The ETSs of precipitation forecasts in terms of various thresholds (in mm). Curves denote scores for the 6–12-hr accumulated rainfall forecasts for experiments CNTL (control run with default values), NC (no convective parameterization), KF (using optimized parameter in the KF scheme), AF (using optimized parameter in the Asselin filter), and KF-AF (using optimized parameters from both the KF scheme and the Asselin filter)

Asia and nearly saturated up to the mid-troposphere; thus resulting in a smaller amount of CAPE, especially prior to and during heavy rainfall (see Lee et al., 1998; Hong, 2004). Therefore, in applying the KF scheme to convective rainfalls in the East Asia, it might be essential to assume slow or almost no consumption of the pre-existing CAPE (e.g., Saito et al., 2006); however, it does not necessarily mean that the KF scheme is not applicable to the QPF study in this region.

Compared with the no-convective parameterization experiment (i.e., NC), the KF scheme revised with the GA-estimation (i.e., KF) shows much higher ETSs at thresholds larger than 40 mm (see Fig. 3). It suggests that the KF scheme is still useful but with an optimized value of ε in accordance with the environment that consumes the CAPE slowly for a heavy rainfall event in the East Asia.

The revised Asselin filter (i.e., AF; $\nu = 0.25$) also brings about improvement in the ETSs for thresholds of 15–50 mm. Generally, the Asselin filter with $\nu = 0.25$ removes $2\Delta t$ waves and reduces the amplitude of $4\Delta t$ waves by one-half, but with little effect on longer-period waves; that is, it acts as a low-pass filter in time. In contrast, the Asselin filter with default value ($\nu = 0.1$) serves as a high-pass filter so that some short-period waves, including gravity waves, are not filtered out. Although the Asselin filter is used for the purpose of numerical stability, the result indicates that its impacts on the QPF are considerable; thus it should be treated with care.

The experiment using both parameters estimated through the GA (i.e., KF-AF) produced the highest ETSs for almost all thresholds, exceeding 0.6 at thresholds lower than 45 mm. It is notable that the QPF skill increases prominently when two revised parameters are used together in the model. This suggests that simultaneous optimization and use of all uncertain parameters, both physical and computational, are essential in improving model performances.

Figure 4 represents a 6-hr accumulated rainfall for the forecast time from 6 to 12 hr for two experiments: (1) with the default values (i.e., $\varepsilon = 0.9$, $\nu = 0.1$; Fig. 4b) and (2) with the GA-estimated values (i.e., $\varepsilon = 0.01$, $\nu = 0.25$; Fig. 4c). During the 6-hr period between 1200 UTC and 1800 UTC 26 June 2005, a heavy rainfall occurred in the west-central part of the Korean peninsula with a local maximum of 100 mm in Seoul (Fig. 4a). The default experiment failed to simulate the amount of rainfall – only 25 mm at the region where more than 90 mm is observed (cf. Fig. 4a and b). Meanwhile, the experiment with the GA-estimated parameters simulated the localized heavy rainfall quite well with 70 mm peak rainfall (cf. Fig. 4a and c).

Overall, it is notable that optimization of parameters improves the QPF significantly, in both location and amount of rainfall, especially when two optimized parameters are used simultaneously. In the selected heavy rainfall case, the closure assumption of the KF scheme is reduced from 90% (default) to 1% while the Asselin filter coefficient is adjusted from 0.1 to 0.25 after optimal estimation.

The uniqueness problem in parameter estimation is ultimately related to the issue of parameter identifiability (Navon, 1997). Since the GA is basically a random search algorithm, the parameter indentifiability can be assessed by repeating the GA run, each composed of 200 MM5 runs (i.e., 10 generations $\times$ 20 chromosomes), until the best chromosomes start to repeat with some regularity.

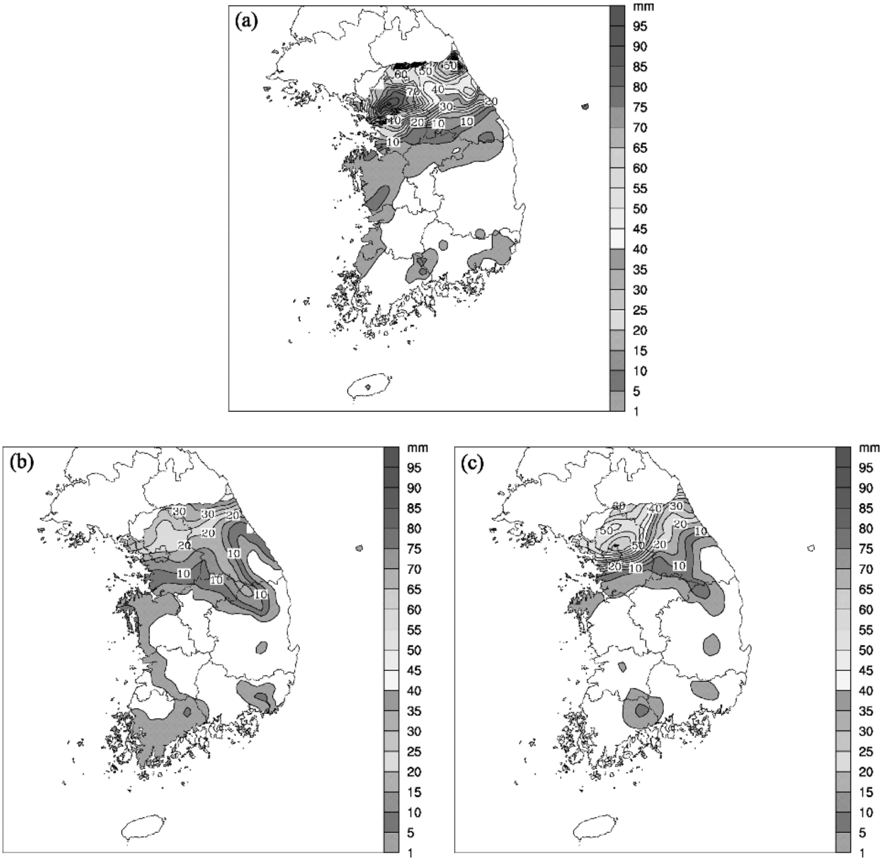

Fig. 4 A 6-hr accumulated precipitation (in mm) of (**a**) observation, and experiments with (**b**) the default parameters and (**c**) the GA-estimated parameters, ending at 1800 UTC 26 June 2005. The model output is interpolated to the rain gauge locations for verification

5 Conclusions

In this study, optimal estimation of parameters in a mesoscale meteorological model (MM5) is performed in the purpose of improving the QPF skills for a heavy rainfall case in the Korean peninsula, employing a global optimization technique called the genetic algorithm (GA). The GA is applied to find out optimal parameters directly using the QPF skill score as a fitness (cost) function.

The GA is robust to complexity and nonlinearity in the model and thus providing more flexible and direct way of solving in parameter estimation. Therefore, nonlinear relations between the fitness function and the model parameters are well treated in the GA. However, the evolution in GA must accommodate physical constraints associated with development and growth so that all possible paths would not be searched in the genetic parameter space (see Deb, 2000).

The model parameters selected for optimal estimation are the reduction rate of the convective available potential energy (CAPE) in the Kain-Fritsch (KF) scheme, ε, for convective parameterization (i.e., physical parameter) and the Asselin filter coefficient for numerical stability, ν, (i.e., computational parameter). The optimized solutions are $(\varepsilon, \nu) = (0.01, 0.25)$. The GA discovered and populated the best regions in the search space only in a few generations.

Each optimized parameter similarly exerted a favorable influence on the heavy rainfall forecast by improving the QPF skill. Further significant improvement in the QPF skill was achieved when two optimized parameters were used simultaneously in the model. This implies that an interaction between optimized physical and computational parameters works favorably to bring about potentially best performance of a numerical model. Therefore, optimizations of computational parameters as well as physical parameters and adequate use of optimized parameters are essential in improving model performance.

It is noteworthy that the optimally-estimated reduction rate of the CAPE in the KF scheme is much smaller than the default value, which is consistent with previous studies depicting slow consumption of pre-existing CAPE in the heavy rainfall cases in the East Asia (Lee et al., 1998; Hong, 2004); thus representing well the characteristic of the selected rainfall environment. Such tendency in the KF parameter will be further investigated with more heavy rainfall cases at least near the Korean peninsula.

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