Scheme-Based Optimization of Land Surface Model Using a Micro-Genetic Algorithm: Assessment of Its Performance and Usability for Regional Applications

Seungbum Hong1,*, Seon Ki Park1,2,3,4, and Xing Yu5

1Center for Climate/Environment Change Prediction Research, Ewha Womans University, Seoul, Korea
2Severe Storm Research Center, Ewha Womans University, Seoul, Korea
3Department of Environmental Science and Engineering, Ewha Womans University, Seoul, Korea
4Department of Atmospheric Science and Engineering, Ewha Womans University, Seoul, Korea
5Tropical Marine Science Institute, National University of Singapore, Singapore

Abstract

Typical parameter calibration techniques in land surface models often limit to solve the spatiotemporal discrepancy of modeling performances due to high heterogeneity of land surface, especially for regional applications. We evaluated a coupling system of micro genetic algorithm (micro-GA) and the Noah land surface model with multi-physics options (Noah-MP) for its usability for regional applications. Four different regions having different climatic characteristics over East Asia were selected, and for each region Noah-MP provides two to four scheme options in eight scheme categories each of which represents different land surface processes, and the model was optimized through searching the best scheme combination by micro-GA. The optimization focussed on the surface water balance, comparing model simulations of evapotranspiration and runoff with the European Centre for Medium-Range WeatherForecasts ERA-Interim land products. The optimizing process was controlled by micro-GA using natural selection and evolution techniques. This study demonstrated that the coupling system assures not only the effectiveness of the scheme-based optimization but also the skill of the used model diagnosis in quantifying model performance during the micro-GA evolution process. Since each region has its own advantageous scheme combination, multiple scheme-combinations are a possible solution for the spatiotemporal discrepancy of modeling performance.


1. Introduction

Uncertainties in land surface models (LSMs) are generally inevitable due to our insufficient knowledge about the governing physical processes, and thus they generally produce unreasonable representation of spatiotemporal surface heterogeneity. Hence, regional applications of such models generally require space and time dependent optimization processes through parameter calibrations. Generally selective parameter calibrations are conducted after model sensitivity tests (Gupta et al. 2000; Jackson et al. 2003; Mo et al. 2008; Nasonova et al. 2011; Rosero et al. 2010; Williams and Maxwell 2011). There are several methods to deal with multiple parameter calibrations. For example, Moriasi et al. (2007) conducted parameter calibration in every scheme in a stepwise way. More effective ways are optimizations using intelligent tools such as genetic algorithm (GA) which uses the evolution process concept through natural selection and mutation mechanism (since Holland, 1975). Recent model development has greatly improved the model skill but also caused higher complexities, increasing the number of model’s uncertain parameters. Moreover, different ways to physical processes such as surface water and heat budget even more increase the complexity of the optimization process. In order to obtain reliable model performances, multiple parameter calibrations such as through GA approaches are demanded.

Before parameter calibrations, however, it is also necessary to check the model characteristics related to the interactions among implemented schemes. Rosero et al. (2010) revealed that parameter sensitivities of a LSM vary with land cover types as well as scheme implementations. This implies that multiple schemes and their interactions have to be considered in the optimization processes. In addition, this previous study brings a conclusion that LSMS have limited applicability especially to large areas because they should deal with regional surface heterogeneity.

Hong et al. (2014) designed a coupling system of a LSM with multi-scheme selections and a GA, enabling scheme-based optimization (optimization through seeking the best scheme combination). Through the optimization process, this system allows to diagnose the simulating performance of each implemented scheme not only in its own capability but also in the interrelationships with the other schemes. Through a test of this coupling system, they showed how the simulating performances vary with scheme combinations, what scheme combination will be advantageous for the following parameter calibration, and what strengths and/or weaknesses in simulating performance each scheme has within the scheme interrelationships. Moreover, they showed that the system is advantageous to solve optimization conflict among multi-variable optimizing targets. For example, evapotranspiration (ET) and runoff that are mutually connected in terms of surface water partitioning take opposite pathways in an evolving process in GA. In other words, the two variables show adverse effects each other in their optimization processes. The authors showed, however, that the coupling system enables us to make an optimized output for two variables in a way of alleviating the conflict problem.

This system now needs to be further evaluated for more extensive applicability to larger or multiple regions in terms of model representation of surface heterogeneity. For this reason, we evaluated the coupling system at four regions in East Asia. Each region shows different hydro-climatic characteristics. The main goal of this work is to answer the following questions: 1) How does the optimization system performs over different regions? 2) How do each scheme performs over different regions? 3) How does the output from the optimization system can be used to describe land surface model errors and their spatial variability? Our optimization target is surface water partitioning: ET and runoff. Comprehensive evaluation related to the research questions above was conducted according to the results from separated optimizations for each selected region.
2. Methods

2.1 The coupling system of a LSM with multi-scheme selections and a GA

The previous study, Hong et al. 2014, used a new version of the Noah LSM with multiple physics options (hereafter Noah-MP) for the scheme-based model optimization. Developed from Noah LSM 3.0v, Noah-MP provides multiple options for the representation of different land surface processes (Niu et al. 2011). We selected 8 land surface processes for the scheme-based optimization. The selected schemes represent the effects of (1) surface roughness length on the heat transfer, (2) supercooled liquid water in frozen soil, (3) frozen soil permeability, (4) snow surface albedo, (5) runoff and groundwater, (6) vegetation gaps for radiation transfer, (7) rainfall and snowfall partitioning, and (8) soil moisture factor for controlling stomatal resistance. The summary of the selected categories and brief descriptions of each available scheme were provided in Table 1. The total possible number of scheme combination becomes 1,728. More detailed information including equations and parameter settings are referred to in the previous studies (Hong et al. 2014; Niu et al. 2011).

Micro-Genetic algorithm (Micro-GA) controls scheme selections of Noah-MP in the coupling system (hereafter MP-MGA).

<table>
<thead>
<tr>
<th>Physical Processes</th>
<th>Options</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>Surface exchange coefficient for heat, (SFC)</td>
<td>(1) Noah type</td>
<td>Chen et al. 1997</td>
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<tr>
<td></td>
<td>(2) Monin-Obukhov scheme</td>
<td>Brutsaert 1982</td>
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<td>Superooled liquid water in frozen soil (FRZ)</td>
<td>(1) Generalized freezing-point depression</td>
<td>Niu &amp; Yang 2006</td>
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<td></td>
<td>(2) Variant freezing-point depression</td>
<td>Koren et al. 1999</td>
</tr>
<tr>
<td>Frozen soil permeability (INF)</td>
<td>(1) Defined by soil moisture</td>
<td>Niu &amp; Yang 2006</td>
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<tr>
<td></td>
<td>(2) Defined by liquid water volume</td>
<td>Koren et al. 1999</td>
</tr>
<tr>
<td>Snow surface albedo (ALB)</td>
<td>(1) BATS</td>
<td>Dickinson et al. 1993</td>
</tr>
<tr>
<td></td>
<td>(2) CLASS</td>
<td>Verschelde 1991</td>
</tr>
<tr>
<td>Runoff and Groundwater (RUN)</td>
<td>(1) SIMGM</td>
<td>Niu et al. 2007</td>
</tr>
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<td></td>
<td>(2) SIMTOP</td>
<td>Niu et al. 2005</td>
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<td></td>
<td>(3) Free-drainage scheme</td>
<td>Schaeke et al. 1996</td>
</tr>
<tr>
<td></td>
<td>(4) BATS</td>
<td>Yang &amp; Dickinson 1996</td>
</tr>
<tr>
<td>Soil Moisture Factor controlling stomatal resistance, β factor (BTR)</td>
<td>(1) Noah type</td>
<td>Chen et al. 1996</td>
</tr>
<tr>
<td></td>
<td>(2) CLM type</td>
<td>Oleson et al. 2004</td>
</tr>
<tr>
<td></td>
<td>(3) SSiB type</td>
<td>Xue et al. 1991</td>
</tr>
<tr>
<td>Two-stream radiation transfer (RAD)</td>
<td>(1) Canopy gaps from 3-D structure and solar zenith angle</td>
<td>Niu &amp; Yang 2004</td>
</tr>
<tr>
<td></td>
<td>(2) no canopy gap</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3) Gaps from vegetated fraction</td>
<td></td>
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<tr>
<td>Partitioning precipitation into rain and snow (SNF)</td>
<td>(1) Complex functional form</td>
<td>Jordan 1991</td>
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<td></td>
<td>(2) Snowfall at ( T_{ar} &lt; T_{ar} + 2.2 ) K</td>
<td>Niu et al. 2011</td>
</tr>
<tr>
<td></td>
<td>(3) Snowfall at ( T_{ar} &lt; T_{ar} )</td>
<td></td>
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Micro-GA is an improved and simplified version of genetic algorithms that have been developed for cost-effective solution of model optimizations using natural genetic variation and natural selection concepts (Holland 1975; Mitchell 1998; Wang et al. 2002; Hu et al. 2006). More specifically, Noah-MP undergoes evolution process by Micro-GA through the following steps. 1) Micro-GA generates multiple sets of eight-discrete-number combination in which each number presents a selection in a scheme category. We set ten for the number of scheme combination; a group of the ten sets is called a generation. 2) Micro-GA makes an ensemble of runs of Noah-MP through applying each scheme combination one by one to Noah-MP by editing the system input file of the model. 3) During the series run, Micro-GA evaluates each simulation through the comparison with reference data based on a given fitness function (see the next section). 4) Based on the scheme combination showing the best performance, Micro-GA generates another 10 sets of offspring scheme combinations through crossover mechanism. 5) The processes above continue until the entire iteration converges into the global maximum (true optimization). Since Micro-GA uses a special sampling technique, it may converge to a local maximum (false convergence). In order to avoid false convergence, the system allows reinitialization based on random selection. Once the system converge to either of local or global maximum, it is reinitialized based on a random scheme selection, but keeping the elite individual from the previous iteration. While the generations undergoes in an evolution process by approaching a maximum point in their averages of the fitness function, the number of crossover for scheme selections decreases. When the number of crossover passes the preset criterion (less than 5% of the total possible number of crossover in a generation), the reinitialization procedure is activated. If an optimization process does not pass through the reinitialization procedure, this indicates that a larger number of generations may need to be set or that the optimization never reaches a stable maximum point.

2.2 Fitness function

Since the evaluation procedure is a critical part during the optimizing process in Micro-GA, it is surely better to use different statistical indices such as correlation coefficient and root mean square error for more reliable model evaluation. However, because GA uses only one fitness function, it should be very careful to select a more comprehensive evaluation technique. As our experiments focused on surface hydrology, our careful selection for the best reliable model evaluation was the Nash-Sutcliffe efficiency (NSE) (Nash and Sutcliffe 1970). NSE, which is a highly recommended evaluation technique for the hydrological modeling fields (Moriai et al. 2007) is a normalized statistic that evaluates the performance of a model with respect to a certain variable. Fundamentally, this index for a given variable (NSE\(_{var}\)) is calculated as follows:

\[
NSE_{var} = 1 - \frac{\sum_{i=1}^{n} (Ref_i - Var_i)^2}{\sum_{i=1}^{n} (Ref_i - \text{Ref mean})^2}.
\]

Ref\(_i\) and Var\(_i\) are the reference data and the model output at a given time step, respectively, and Ref mean is the temporal mean of the reference data. Including the term of the mean square error, NSE evaluates simulation performance in quantifying the differences both in means and variations between the observation and simulation (Legates and McCabe 1999). The closer to one NSE is, the better performance model simulation is. Over 0.5 of NSE is generally accepted that the simulation is satisfactory.

Since we are focusing on surface water partitioning, NSE needs to be modified in order to evaluate multiple variables. Thus, targeting two basic surface water components, evapotranspiration (ET) and runoff, a multivariable NSE (mNSE) can be simply obtained by adding the NSEs of the two variables (mNSE = NSE\(_{ET}\) + NSE\(_{RUN}\)). Then, mNSE ranges from 2 (perfect agreement) to negative infinity.
2.3 Study domains and data

As atmospheric forcing input for Noah-MP, six meteorological fields from Global Land Data Assimilation System (GLDAS) data (Rodell et al. 2004) were used such as precipitation, downward short and longwave radiation, near-surface air temperature, near-surface wind speed, and surface pressure. The 10-year GLDAS forcing data from 2001 to 2010 was used for the model simulation. As shown in Fig. 1, four regions that have different climatic characteristics were selected based on precipitation regimes for the regional applications of MP-MGA: (1) Korean Peninsula (RE1), (2) East Siberia (RE2), (3) Gobi Desert (RE3), and (4) a southern part of China (RE4). The different climates in the four regions are as follows: semi-humid (RE1), semi-arid (RE2), arid (RE3), and humid (RE4).

For the multi-variable evaluations, ERA-Interim was used as the reference data (Dee et al. 2011). ERA-Interim produced by the European Centre for Medium-range Weather Forecasts (ECMWF) is a global atmospheric reanalysis describing the states of the atmosphere, land, and ocean waves, which employed the four-dimensional variational data assimilation. As the land surface component, ERA-Interim used the Tiled ECMWF Surface Scheme for Exchange over Land (Van den Hurk et al. 2000; Viterbo and Beljaars 1995; Viterbo et al. 1999). The ECMWF provides very accurate and reliable global atmospheric reanalysis. The land surface model coupled with the atmospheric model in ECMWF produces well balanced surface water budget.

Comparison between models and ERA-Interim data is performed using the daily and domain averaged mNSE computed for each particular region. The actual spatial and temporal resolutions in the simulations were 0.25 degrees and 3 hours, respectively. The first 6-month outputs (July to December, 2000) were excluded as the period for the model initialization (or spin-up).

3. Applications of MP-MGA to East Asia regions

Full 10-year simulations using MP-MGA with 15 generations were performed for the four study regions in East Asia. Thus, 150 simulations in all were performed for each region. Figure 2 shows how the generations evolve during the Micro-GA iterations for each study region, presenting the mNSE averages (the Y-axis) of the generations each of which comprises 10 scheme combinations. The timings of the first convergence points of all regions did not show any significant differences, occurring between 8th to 10th generations. The sudden drops of the average mNSE value right after the first converging points (the 10th generation in the RE1 and RE2 results) are the restart point of the evolution processes as explained in Section 2.1. Once Micro-GA converges into either of local or global maximum, it restarts the evolution process with a new generation with the finally-survived individual plus random selections in order to avoid any false optimization. The gradual degeneration of RE3 and RE4 in Fig. 2 indicates that Micro-GA failed to reach a generation convergent point at which the system can activate the reset procedure. In this case, Micro-GA found the optimized scheme combination, but the final output is unstable.

Separate Micro-GA experiments for ET and Runoff based on the normal NSE and those based on mNSE for both variables showed repercussion effects in all regions as shown in the previous study (Hong et al. 2014). For example, while the NSE_{ET} optimization for RE2 showed the best result with 0.82 of NSE_{ET}, that simulation from the same scheme combination resulted in 0.06 of the NSE_{RUN} that is much lowered one, compared with 0.22 of NSE_{RUN} from the NSE_{RUN}−based optimization.

Figure 3 shows the final (the best and worst) MP-MGA outputs from mNSE-based optimization, and Table 2 summarizes the selected schemes showing the simulation performance for each region. The results showed that the scheme combinations varied with the region, possibly in association with the regional climate. Having moderate climate conditions, RE1 and RE2 showed relatively reasonable performances in the runoff and ET simulations. According to the information from the natural selection mechanism of Micro-GA, the schemes that mainly contributed to the accuracy achievement were RUN (1), ALB (2), and SFC (1) for RE1. As shown in Fig. 3, the best extracted runoff outputs were consistent with the reference data, and the best extracted ET outputs showed reasonable performance during summer but underestimation during winter. To improve the model estimation of the winter ET for this region, parameter optimizations within the
extracted schemes may be required, especially for those involved with winter variations (e.g., the ALB schemes). RE2 also shows good performances in ET simulation but an underestimation of the runoff. In this region, compared to RE1, the overall model performance was strongly affected by the ET simulation. The schemes that contributed most to the achievement of the best mNSE over RE2 were SFC(1) and INF(1), which are considered to be mainly involved in the ET simulations. From the comparisons of the best and worst runoff simulations, it is inferred that the choices of schemes and/or their combinations affect not only the systematic errors but also the temporal variations.

On the other hand, RE3 and RE4 showed relatively worse simulation performances. No scheme choices or their combinations for ET over RE3 had any positive influence on reasonable ET simulations. However, the MP-MGA optimization produced reasonable acquisition of surface water partition by reducing the runoff overestimation. While RE4 performed relatively well in the runoff variability, ET performance showed as a seasonal cycle which is far from the one obtained from the ERA-Interim. The schemes related to the ET estimation may need to be improved with further parameter optimization for reasonable ET seasonality.

It is notable that the scheme used for the computation of the land-atmosphere heat exchange coefficient (SFC) was important for the optimization of the water budget in all regions except RE3. This is because heat fluxes play a significant role in the surface energy balance directly affecting the magnitude of ET and runoff.

4. Summary and conclusion

In this study, we evaluated the applicability of the MP-MGA coupling system to regional applications, seeking the three main scientific questions. Four different regions in East Asia were selected, and MP-MGA was applied to see how different the optimization processes are with the regions as the first scientific question. The number of generations required to reach convergence was similar over the four regions, but it will be safer to have more iterations in the optimization process for some regions in order to ensure that the final output results from the global maximum. This variance is likely to be associated with the variance in performance of each scheme as the second scientific question. In other words, these experiments showed which scheme is more helpful to obtain better accuracy. The different scheme choices for each region may reflect its different hydrological characteristics.

The ultimate model optimization would be completed with additional parameter calibration, and the MP-MGA approach will be very useful to find a base model which is specialized for local characteristics or at least to quantify model performances of each scheme in the interrelationship with the other schemes. For example, the cases that showed reasonable performances such as RE1 and RE2 regions will provide us with an effective starting point for further parameter calibrations (e.g., for improvement of the underestimate of the winter ET in RE1). However, there were some cases that showed very poor performances such as RE3 and RE4 regions. These indicate that any implemented schemes used in this study are not suitable for such regions. For example, especially for RE3 the schemes may need to be further improved to catch small variations of surface hydrology under such a dry condition. For these cases the schemes that are the most important for simulation performances such as SFC schemes may be a starting point for further improvement. In addition, we still cannot ignore that the final optimized output from this study can be applicable only to the ERA-Interim data, so it is very cautious that anyone uses the output without further validation. These results have to be further validated using real observations. Nonetheless, this study is worthy of attention because it shows that each region will have its own optimized scheme combination and even the simulating performances will vary. This indicates that it is very difficult to reduce the regional discrepancies of models’ simulating performances only with parameter optimizations. In order to minimize the spatiotemporal discrepancy of model’s simulating performances (the third scientific question), the model might need to have multiple scheme-combinations, each of which is specifically optimized for a certain region.

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Table 2. The best scheme combinations extracted from MP-MGA for each region. The bold-text schemes indicate the most contributing ones to the simulation accuracy based on mNSE.

<table>
<thead>
<tr>
<th>Region</th>
<th>Scheme Combination</th>
<th>mNSE</th>
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<tbody>
<tr>
<td>RE1</td>
<td>SFC(2); FRZ(2); INF(2); ALB(2); RUN(1); SMF(2); RAD(3); PRT(1)</td>
<td>0.64</td>
</tr>
<tr>
<td>RE2</td>
<td>SFC(1); FRZ(2); INF(1); ALB(2); RUN(2); SMF(1); RAD(2); PRT(3)</td>
<td>0.98</td>
</tr>
<tr>
<td>RE3</td>
<td>SFC(1); FRZ(2); INF(1); ALB(2); RUN(4); SMF(1); RAD(1); PRT(2)</td>
<td>−0.39</td>
</tr>
<tr>
<td>RE4</td>
<td>SFC(2); FRZ(2); INF(2); ALB(1); RUN(1); SMF(3); RAD(3); PRT(1)</td>
<td>0.07</td>
</tr>
</tbody>
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References


Jordan, R., 1991: A one-dimensional temperature model for a snow cover. Technical Documentation for SNTHERM.89, Cold Regions Research and Engineering Lab, Hanover, NH.


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