

Optimal Parameter and Uncertainty Estimation for Climate Model Prediction using Multi-Level Dual-Annealing Stochastic Approximation Monte Carlo Algorithm

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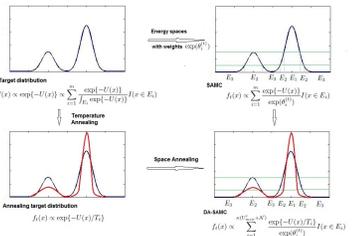
Motivations

- Uncertainties of climate model are mainly from uncertainties of unresolved physics processes, e.g. physics scheme and parameters;
- Models are tuned towards the mean of observation, but there may exist compensation errors, which may no longer compensate when moving to a new climate regime. Parameters error may also compensate with each other;
- Climate model's result depends nonlinearly to the combined changes in model parameters;
- The Optimal parameters usually are scale-dependent.

Research Objective & Outline

Objective:	Outline:
► Studying sensitivity of physic processes and simulations to parameters in climate model	► DA-SAMC Algorithm
► Reducing errors and deriving scare-aware optimal parameters used in cloud convection scheme	► Simulation & Results
	► Conclusion & Discussion

DA-SAMC Algorithm



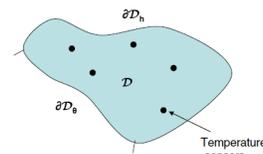
- Energy Space
 - $U(X): X \rightarrow E$
- Weights $\exp(\theta_i^{(t)})$
- Self-adjusting mechanism
- DA-SAMC
 - Temperature Annealing
 - $T_i = T_0 \times \alpha^{i-1}$
 - Space annealing
 - Shrinking sampling space at each iteration based on the best cost value obtained so far
 - $\kappa(U_{min} + N)$

Simulation & Results

1) 2D Temperature Sensor Inversion

- Observe: A 6*6 grid, 6 observations with error on each grid point.

- Problem: Use those observations to estimate the boundary temperature T_1 and T_2



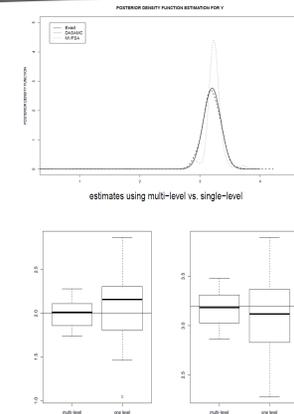
$$U_{xx} + U_{yy} = 0$$

$$U_x(0, y) = q_1$$

$$U(x, 0) = T_1$$

$$U_x(1, y) = q_2$$

$$U(x, 1) = T_2$$

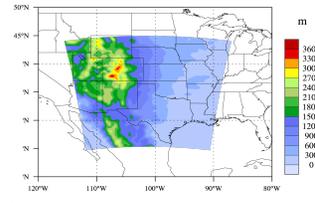
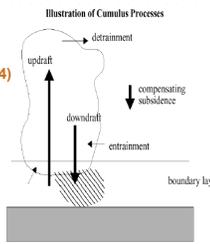


- With the increasing of the number of grids, the computational cost to get one numerical solution increases dramatically.
- Perform DA-SAMC on coarse grid can give a good rough estimate at a relatively small computation cost.
 - Coarse grid: 4*4 with 2 obs/point
 - Fine grid: 12*12 with 2 obs/point
- Single level:
 - 20 steps on fine grid
- Multi-level:
 - 100 steps on coarse grid
 - 10 steps on dense grid
 - Takes less computation time
 - Give more accurate results

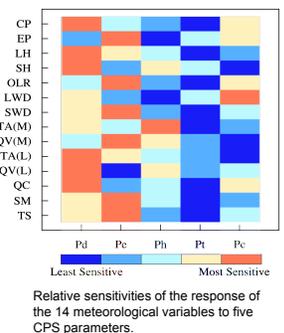
2) WRF regional climate model Inversion

Parameters of Kain-Fritsch Cumulus scheme (Kain, 2004) Weather Research and Forecasting Model (WRF3.2)

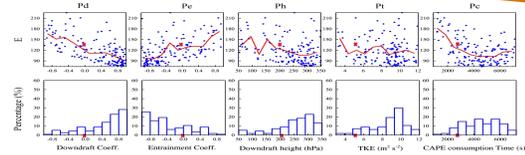
- Updraft velocity
- Downdraft Mass Flux Rate
- Environmental Air Entrainment Rate
- Consumption Time of CAPE



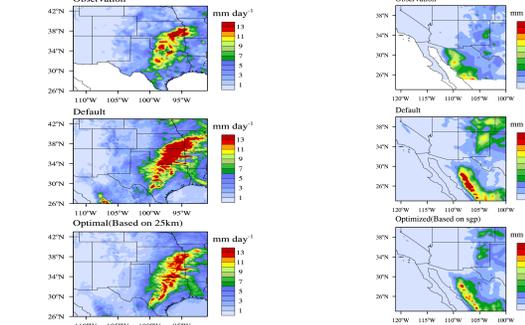
WRF model domain (Southern Great Plain, 25°N-44°N and 112°W-90°W) with grid spacing of 25 km. Shades indicate the terrain (Unit: m).



Relative sensitivities of the response of the 14 meteorological variables to five CPS parameters.



(Top) The response of model performance to five input parameters (Bottom) The frequency distributions of "good" experiments as function of each parameter.



The spatial distributions of observed and WRF simulated (with 12-km spatial resolution) monthly mean precipitations for June of 2007, with default and optimal parameters. The spatial distributions of observed and simulated monthly mean precipitations with default and optimal parameters obtained at SGP, respectively, over North America Monsoon (NAM) region for July of 1991.

Conclusions and future work

- Multi-level DA-SAMC algorithm features:
 - Efficient Bayesian model parameter calibration, which can greatly speedup the convergence and dramatically reduce the number of ensemble runs;
 - The proposed method is a scare-aware model parameter calibration method – it first uses coarse-resolution model to obtain a estimation of the uncertain parameter posterior distribution; then use it as a prior for fine-resolution model for fast convergence and computational efficiency enhancement;
 - The multi-level dual-annealing SAMC method can guarantee to find the global optimal parameter estimation and avoid local trapping, which limits the convergence of Very Fast Simulated Annealing (VFSA) method.
- Parameters such as Downdraft, Entrainment and Cape Consumption Time show very important impact on convective precipitation.
- Although only precipitation is constrained in this study, other climatic variables are controlled by the selected parameters so could potentially be benefited by the optimal parameters used in convective cloud scheme.



Acknowledgements
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