A systematic study of parameter dependence in the ICTP AGCM

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ABSTRACT

The ICTP Atmospheric General Circulation Model is used to investigate basic issues in model parameter dependence and to develop a parameter optimization scheme. Climate models present several challenges for optimization arising from high-dimensionality, computationally-expensive simulations, and ambiguity in the choice of the objective function.

A first analysis with the ICTP AGCM suggests that many climatic variables of interest it yield objective functions, such as root mean square error of the climatological spatial field, that vary fairly smoothly through the parameter range explored. Low order polynomial fits to the model output as a function of parameter (quadratic in model field, 4th order in cost function) are thus surprisingly successful for many quantities. Optima frequently occur at the end of the feasible parameter range, implying a constrained optimization problem---this also suggests a means for identifying parameterization aspects in particular need of physical scrutiny. Furthermore, optima for different variables tend to occur at different parameter values. Treating this as a multi-objective optimization problem thus yields much more information for the climate modeler. Objective functions constructed from the fit to the complex climate model (and permitting approximations yielding reduction in the number of climate model evaluations required) make this feasible.

MODEL

- ICTP AGCM (Molteni F., 2003, Climate Dyn. **20**, 175-191; Bracco et al. 2004, Climate Dyn. **23**, 659-678**)**
- Spectral dynamical core
- Eight Sigma-levels, spectral triangular truncation at total wave number 30 (T30), roughly equivalent to a 3.75 x 3.75-degree
- Convection occurs in a conditionally unstable region when humidity in the boundary layer exceeds a prescribed threshold
- Large-scale condensation and shallow convection
- Shortwave radiation scheme uses two spectral bands
- Long-wave radiation scheme uses four spectral bands
- Bulk aerodynamics formulas for surface fluxes
- Estimation of cloud cover and its thickness
- http://users.trieste.it/~atmos_sw/gcm/speedy8_clim.html

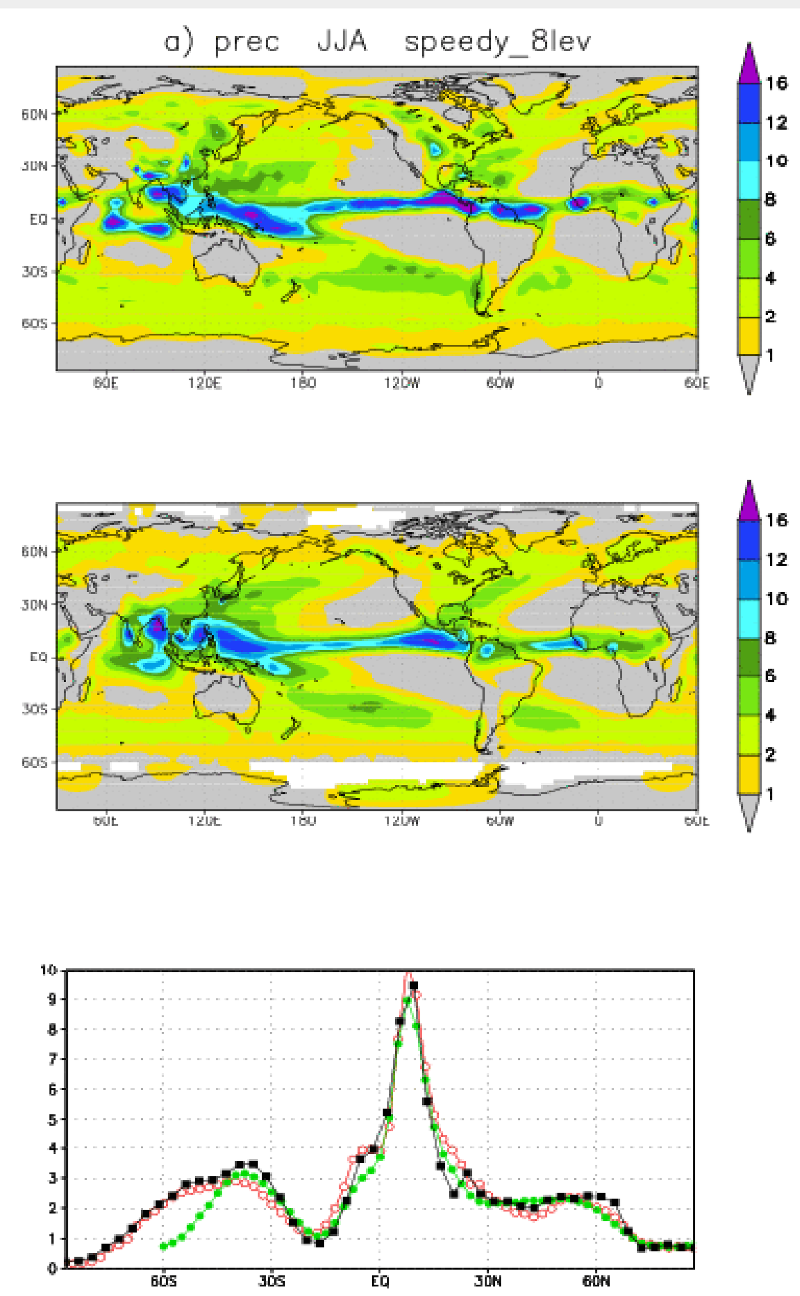

Figure 1: 1978-2002 precipitation climatology (in mm/day) from the ICTP AGCM standard integration (top) and from the CMAP (Xie-Arkin) (middle) in boreal summer. At the bottom zonal mean values are shown with model in black, CMAP climatology in green, ERA-15 climatology in red.

PARAMETER SPACE SECOND ORDER FIT

To provide examples of the parameter space dependence we selected four parameters known to impact the model solution: the **subgrid scale wind gustiness** that controls the minimum wind speed in the bulk formula for surface fluxes; the **relative humidity** from the deep convective parameterization that controls the moisture towards which the convection adjust the column; the **cloud albedo**; and a **viscosity parameter** measured as a damping time. For any of the four parameters, we chose eight, equally spaced values centered around the standard one. An ensemble of ten simulations 25-yr long and forced by observed sea surface temperatures has been performed for each parameter value and for any possible combination of two simultaneously varying end-points (min-min, min-max, max-min, max-max for any two parameters).

Let μ_i be one of the parameters taken relative to its standard value, i.e., $\mu_i = \mu^*_i - \mu^{std}_i$, where i denotes the parameter, * the original value and μ^{std}_i the value of the standard case. A second order fit on the space of N parameters can be obtained evaluating

$$\tilde{\varphi} = \varphi_{std} + \sum_i^N a_i \mu_i + \sum_{i=1}^N \sum_{j=1}^N b_{ij} \mu_i \mu_j$$

The N diagonal values of b_{ij} can be fit along with a_i from the 2N endpoints of the μ_i ranges. Order 2N integrations are required for the linear and quadratic diagonal elements. The number of model evaluations to obtain off-diagonal b_{ij} is equal to the number is of order N^2. We estimate below the impact of the off-diagonal elements (which correspond to a rotation of the quadratic basin around a minimum).

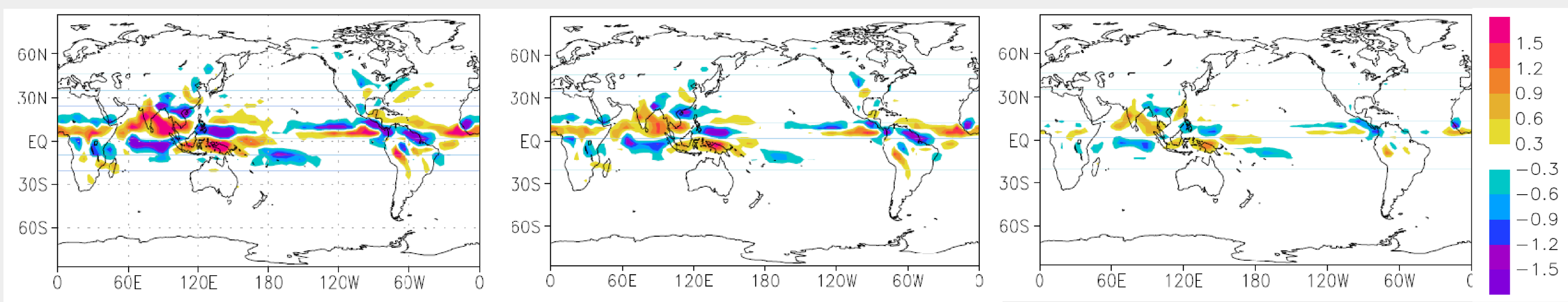

***Figure 2:** (left) Speedy ensemble-mean JJA precipitation (as a departure from the annual mean) change relative to the standard case when convective relative humidity parameter at its maximum value (as a departure from the annual mean, minus standard case); (b) linear contribution $a\mu_i^{max}$ and (c) quadratic contribution $b(\mu_i^{max})^2$. In mm/day.*

This fit can be updated by least-squares estimates of a and b as subsequent ensembles of simulations are performed at points chosen based on the optima or around deep minima of this initial fit. Any quantity from the model output can be examined in this way. Next we reconstruct the RMS error $\left\langle \left[\tilde{\varphi}(\mu_i) - \bar{\varphi}\right]^2 \right\rangle^{1/2}$

<> denotes mean over spatial points using eq. (1) for $\tilde{\varphi}$, and NCEP for $\bar{\varphi}$. In most cases we find modest but not negligible contributions of the quadratic term but in some cases it is large enough to actually reverse the curvature of the objective function.

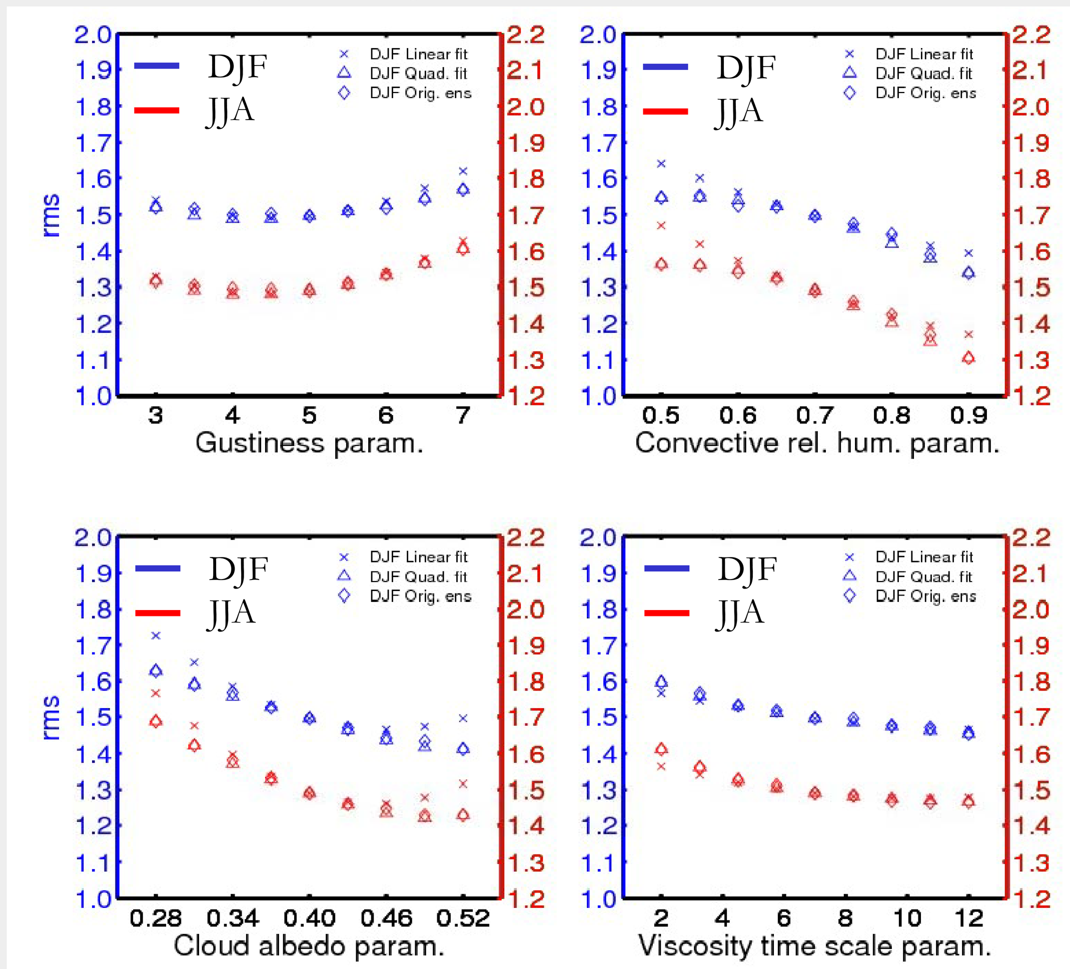

***Figure 3**: Root-mean-square (RMS) error of the ensemble mean ICTP-AGCM precipitation in winter (DJF) and summer (JJA) relative to NCEP reanalysis. Also shown reconstruction from linear and quadratic fits for each modeled parameter investigated.*

Note the negative curvature of the objective function for the relative humidity parameter and the common occurrence of minima at the limit of the parameter range.

OPTIMIZATION PROBLEM

In climate science standard optimization procedures have not been developed so far. On the other hand optimization strategies to solve high-dimensional design problems with computationally-expensive black-box functions exist. Our analysis implies that for large scale measures (such as RMS of climate variables) low order fitting procedures are quite successful. This leads to a constrained optimization problem that allows fast, repeated optimizations using commercially available optimization packages (e.g. KNITRO). This permits multi-objective optimization in which we can consider separate objective functions for each important climate variable, as opposed to considering a cost function that use pre-determined, arbitrary weights (on which different users might disagree) to optimize a sum over many climate variables.

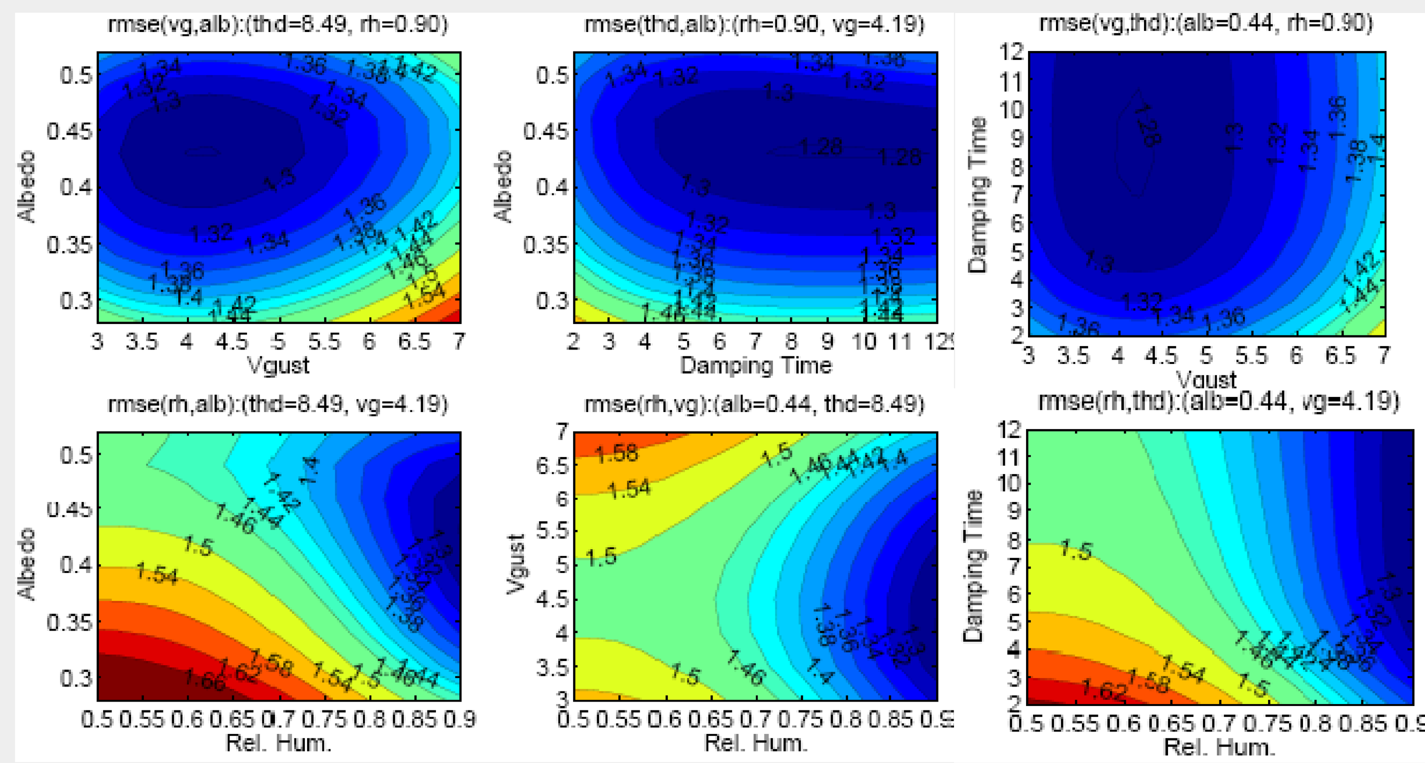

***Figure 4:** RMS error of modeled June-August precipitation relative to NCEP reanalysis, reconstructed from model quadratic fits for two-dimensional slices through parameter space at the global optima at albedo = 0.44, wind gustiness = 4.19, rel. humidity = 0.90, viscosity = 8.49 found using KNITRO nonlinear optimization scheme.*

In tuning a climate model, users frequently encounter improvement in one variable but degradation in others. Figure 5 quantifies the contradiction among objective functions as the location of the optima in parameter space for different climate variables. The spread of the optima in parameter space is substantial. A multi-objective procedure that provides a strict partial order for these optima, i.e. provides information about the trade-offs in optimizing for different variables, provides more information for climate modelers than a blind optimization for a weighted sum. Also shown is the extent to which a fit requiring order *N* climate model evaluations can provide a good approximation versus one requiring order N^2. For most variables an order *N* procedure gives a reasonable approximation.

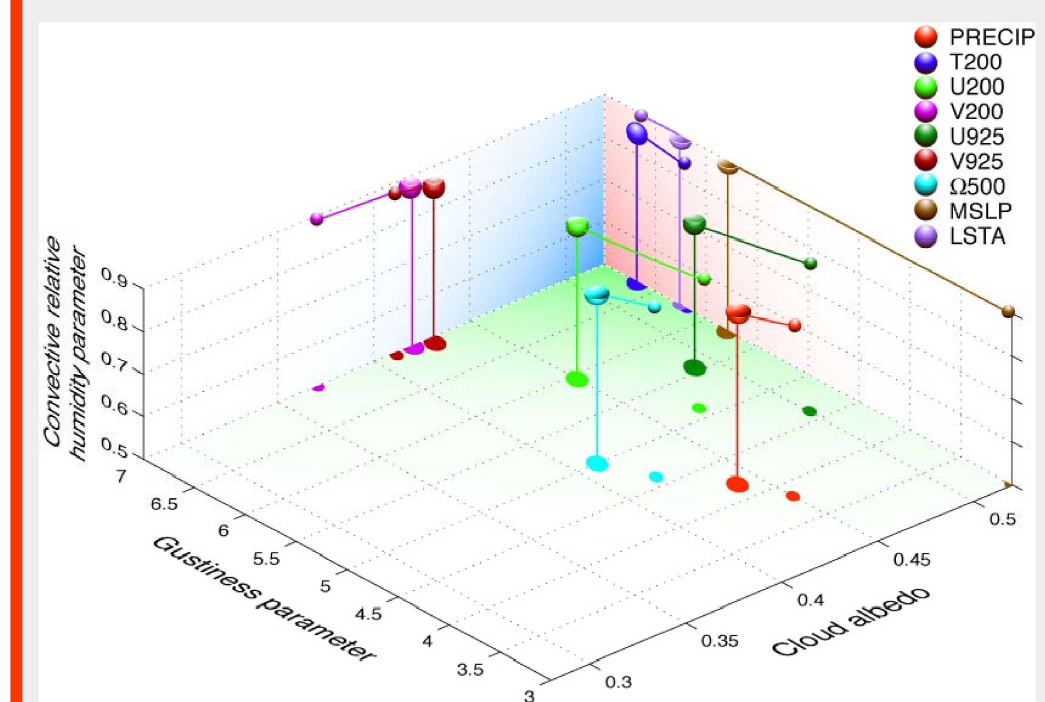

***Figure 5:** Global optima calculated using an order N (large sphere) or order N^2 (small sphere) procedure for RMS error objective functions for several model variables.*

P is precipitation, T is temperature, U, V are wind components, Ω is vertical velocity, MSLP is mean sea level pressure and LSTA is land surface temperature. Levels are in hPa.