Report on activities and findings under DOE grant "An Interactive Multi-Model for Consensus on Climate Change"
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Project synopsis

This project purports to develop a new scheme for forming consensus among alternative climate models, that give widely divergent projections as to the *details* of climate change, that is more intelligent than simply averaging the model outputs, or averaging with *ex post facto* weighting factors. The method under development effectively allows models to assimilate data from one another in run time with weights that are chosen in an adaptive training phase using 20th century data, so that the models synchronize with one another as well as with reality. An alternate approach that is being explored in parallel is the automated combination of equations from different models in an expert-system-like framework.

Results and Primary Activities

The project takes a hierarchical approach. The model-fusion-via-synchronization scheme is new, so there is a fair amount to be learned from the study of the scheme as applied to simple systems of ordinary differential equations (ODEs). Rather than deal with the computational demands of full climate models, the second stage of the project, currently underway, will construct ``supermodels" from simple quasigeostrophic models and somewhat more complex intermediate models. In the final year, a software-intensive activity will apply the scheme to full climate models. Details of the current status are as follows:

Unlike the simplest systems of ODEs, the climate system is characterized by a multiplicity of time scales. It is not *a priori* clear how a supermodel formed from different ocean models and different atmospheric models would be trained. The issue was examined using a 2-box ocean model coupled to a Lorenz `84 atmosphere model, given by the following system of equations:

$$x' = -(y^2) - (z^2) - a\,x + a\,(F_0 + F_1\,T) \qquad f \equiv \omega\,T - \xi\,S$$

$$y' = x\,y - b\,x\,z - y + G_0 + G_1\,(T_{av} - T)$$

$$z' = b\,x\,y + x\,z - z$$

$$T' = k_a\,(\gamma\,x - T) - |f|\,T - k_w\,T$$

$$S' = \delta_0 + \delta_1\,(y^2 + z^2) - |f|\,S - kw\,S$$

where x,y, and z are the Lorenz `84 variables, and T,S are the ocean temperature and salinity gradients. Three copies of the above system were coupled to a single ``truth", in the generic supermodeling framework with fixed nudging coefficients (or more generally, Kalman gains) and connection coefficients adapted according to the general training law

$$dC_x^{ij}/dt = a(x_j - x_i)(x - \tfrac{1}{3}\textstyle\sum x_k)$$

where i,j,k are 1, 2, or 3 (indexing the three models) and x can be replaced by the other variables y, z, T, or S. The three models differ in the parameters a, F_0, F1, b, G_0, G_1, T_{av}, k_a, k_w, γ, δ_0, δ_1, ω, and ξ. Both ocean and atmosphere supermodel variables converged to truth after training, better than an average of the individual model variables, with a very rapid convergence of T and S. But the very rapid convergence of the ocean variables was seen to be due to the fact that while the parameters appearing in the T and S equations are much smaller than the parameters in the x, y, and z equations, the nudging coefficients were of the same order, effectively forcing the ocean models to truth. The simple lesson is that an atmospheric supermodel can be trained using ocean truth or climatology and then an ocean supermodel can be trained on longer time scales.

Supermodeling is achieved, as originally conceived, by introducing nudging terms between corresponding variables in the different models, e.g.

$dx^i/dt = f_x^i(x^i,y^i,z^i) + \sum_j C^{ij}(x^j - x^i)$

using the average over models (that are almost synchronized) , e.g . $x \equiv (1/3) \sum_i x^i$ as the supermodel variable. A stronger form of supermodeling can be imagined, in which one takes linear combinations of the tendencies as prescribed by the different models, e.g. $dx/dt = \sum_i w^i f^i (x^i,y^i,z^i)$, for some set of fixed weights w^i to form the supemodel directly. It was found that this approach was sometimes competitive, although the learning task for the weights can be more demanding.

As the number of independently trained connections increases, there is a risk that the learning algorithm will find locally optimal combinations of coefficients that are significantly inferior to the globally optimal combination. The addition of noise in the training scheme can help avoid such situations and lead to an improved supermodel. A comparison was made between two established machine learning algorithms, one deterministic and the other stochastic that are described in detail in [1]. The algorithms were applied to a simple Lorenz supermodel and the quality of the results was measured using the temporal auto-correlation function for each variable. The deterministic scheme gave autocorrelations resembling the true ones more closely, for all three variables, suggesting that stochasticity, as introduced though the particular algorithms used, is effective for avoiding local optima.

In [2, 4] we introduced improved model that represents interactive ensemble of individual models. The improved model's performance is tested with the Lorenz 96 toy model. One complex model is considered as reality, while its imperfect models are taken to be structurally simpler and with lower resolution. The improved model is defined as one with tendency that is weighted average of the tendencies of individual models. The weights are calculated from past observations by minimizing the average difference between the improved model's tendency and that of the reality. It is numerically verified that the improved model has better ability for short-term prediction than any of the individual models.

Several approaches of ensemble of interacting imperfect models combined based on observed data either by adaptive synchronization, optimized couplings or weighted combining have been proposed and reviewed in [3]. In [3] we examined the weighted combining method using the Hindmarsh-Rose (HR) neuron model and the different outcomes that we can expect. We generated data with an HR model usually referred as 'truth' and used the data to train an ensemble of HR models with perturbed parameter values, so that together they mimic the truth. The results show that the weights of the ensemble can be learned using data from a truth HR model exhibiting bursting, in order to represent the same bursting behavior as well as other behaviors such as spiking and random bursting [3].

Contemporary tools for reducing model error in weather and climate forecasting models include empirical correction techniques. In [5] we explored the use of such techniques on low-order atmospheric models. We presented an iterative linear regression method for model correction that works efficiently when the reference truth is sampled at large time intervals, which is typical for real world applications. Furthermore we investigated two recently proposed empirical correction techniques on Lorenz models with constant forcing while the reference truth is given by a Lorenz system driven with chaotic forcing. Both methods indicate that the largest increase in predictability comes from correction terms that are close to the average value of the chaotic forcing [5].

The question concerns the minimum density of coupling points, should we choose to couple the different models in physical space. The question was investigated using a one-dimensional PDE, the Kuramoto-Sivishinsky (KS) model. It was found [6] that the maximum coupling distance required for synchronizing two KS models, and for coupling them in a supermodel, corresponded roughly to the width of typical coherent structures (fingers) that form in the model. Further, coupling three different KS systems resulted in an effective supermodel with fixed coefficients, and a better one was obtained if the coefficients were adapted according to the scheme described above for Lorenz systems [6].

As ongoing activity, we are constructing supermodels from simple QG models and from more complex intermediate models with which to test a key hypothesis: If the North-South temperature gradient is increased, the inter-model connection scheme found by training with a lower temperature gradient should still be effective. Toward this end, we are using a T42 ``true" system to train a supermodel consisting of T21 models. The SPEEDO model introduces an ocean component.

Publications

[1] Mirchev M, Duane GS, Tang WS, and Kocarev L, 2012: Improved modeling by coupling imperfect models, *Commun. Nonlin. Sci. and Num. Simulation*, 17, 2741-2751.

[2] L. Basnarkov and L. Kocarev, Forecast improvement in Lorenz 96 system, *Nonlin. Processes Geophys*., 19, 569-575, 2012

[3] M. Mirchev M and L. Kocarev L 2014: On the Approach of Ensemble of Interacting Imperfect Models, in *Proceedings of International Conference on Theory and Application in Nonlinear Dynamics* (ICAND 2012), Springer series: Understanding Complex Systems, Springer 2014, pp 327-332

[4] Basnarkov L and Kocarev L, 2014: Interactive Ensembles of Imperfect Models: Lorenz 96 System, in *Proceedings of International Conference on Theory and Application in Nonlinear Dynamics* (ICAND 2012), Springer series: Understanding Complex Systems 2014, pp 39-50

[5] Trpevski I, Basnarkov L, Smilkov D, and Kocarev L, 2014: Empirical correction techniques: analysis and applications to chaotically driven low-order atmospheric models, *Nonlin. Processes Geophys*., 20, 199-206, 2013

[6] Basnarkov L, Duane GS, and Kocarev L, 2014: Generalized synchronization in spatially extended systems, *Chaos, Solitons & Fractals* 59, 35-41

Presentations and Meetings Attended

1) Attended kickoff meeting of the European project: Supermodeling by Combining Imperfect Models, Skopje, Macedonia, Nov. 2010.

2) G.Duane, F. Selten, N. Keenlyside, W. Wiegerinck, J. Kurths, and L. Kocarev, ``Supermodeling" by adaptive synchronization of climate models (poster), Annual Meeting of the European Geophysical Union, Vienna, Austria, April 2011.

3) G.S. Duane, L. Kocarev, and F. Selten: "Supermodeling" climate by combining alternative models, Annual Conference of the National Society of Black Physicists, Austin, TX, Sept. 2011.

4) G. Duane, L. Kocarev, and F. Selten: Consensus among climate models via synchronized chaos, DOE climate modeling PI meeting, Sept., 2011.

5) Session convener: "Supermodeling Climate by Combining Alternative Models", Fall Meeting of the American Geophysical Union, San Francisco, Dec. 2011, with presentations

G. S. Duane and L. Kocarev: Supermodeling by synchronization of alternative climate models

J. Tribbia, G. Duane, I. Trpevski, D. Trpevski, and A. Karspeck: Toward a practical implementation of an interactive multimodel with full GCMs (poster)

6) M. Mirchev and L. Kocarev "On the Approach of Ensemble of Interacting Imperfect Models", International Conference on Theory and Application in Nonlinear Dynamics (ICAND 2012), Washington, USA

7) L. Basnarkov and L. Kocarev, "Interactive Ensembles of Imperfect Models: Lorenz 96 System", International Conference on Theory and Application in Nonlinear Dynamics (ICAND 2012), Washington, USA

8) L Basnarkov, G Duane, and L Kocarev, "Supermodel - Interactive Ensemble of Low-dimensional Models" EGU General Assembly 2013, held 7-12 April, 2013 in Vienna, Austria, p.14076 Publication Date: 04/2013

9) L Basnarkov, G. Duane, and L Kocarev, "Forecast improvement by interactive ensemble of atmospheric models American Geophysical Union", Fall Meeting 2013, abstract #NG31A-1561, 12/2013

Travel

Travel to all of the above meetings and presentations and additionally Travel for Daniel Trpevski (student of Kocarev) to Boulder to work with Alicia Karspeck on software development for the revised DART, April 2011.