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Key Points:
- Multiple AGCMs, coupled to one ocean, are better than any average of separate AGCM-OGCM outputs
- Approximate synchronization of the AGCMs is the key to the improved results
- Salient improvements are in the nonlinear feedbacks as well as in the SST and precipitation fields

Supporting Information:
- Supporting Information S1

Correspondence to:
M.-L. Shen,
maolin.shen@uib.no

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Dynamically combining climate models to "supermodel" the tropical Pacific

Mao-Lin Shen[1], Noel Keenlyside[1], Frank Selten[2], Wim Wiegerinck[3], and Gregory S. Duane[1,4]

[1]Geophysical Institute, University of Bergen and Bjerknes Centre for Climate Research, Bergen, Norway, [2]Royal Netherlands Meteorological Institute, De Bilt, Netherlands, [3]Donders Institute for Brain, Cognition and Behaviour, Radboud University Nijmegen, Nijmegen, Netherlands, [4]Department of Atmospheric and Oceanic Sciences, University of Colorado Boulder, Boulder, Colorado, USA

Abstract We construct an interactive ensemble of two different climate models to improve simulation of key aspects of tropical Pacific climate. Our so-called supermodel is based on two atmospheric general circulation models (AGCMs) coupled to a single ocean GCM, which is driven by a weighted average of the air-sea fluxes. Optimal weights are determined using a machine learning algorithm to minimize sea surface temperature errors over the tropical Pacific. This coupling strategy synchronizes atmospheric variability in the two AGCMs over the equatorial Pacific, where it improves the representation of ocean-atmosphere interaction and the climate state. In particular, the common double Intertropical Convergence Zone error is suppressed, and the positive Bjerknes feedback improves substantially to match observations well, and the negative heat flux feedback is also much improved. This study supports the concept of supermodeling as a promising multimodel ensemble strategy to improve weather and climate predictions.

1. Introduction

Numerical models are the key to the projection of future climate. Through coordinated multimodel ensemble experiments, they provide the scientific basis for the Intergovernmental Panel on Climate Change assessment reports [*Intergovernmental Panel on Climate Change*, 2013]. Despite improving substantially, state-of-the-art general circulation models (GCMs) exhibit significant systematic errors, often common to many models, that have persisted across model generations: e.g., a double Intertropical Convergence Zone (ITCZ) and cold tongue bias in the tropical Pacific, and the eastern equatorial Atlantic warm bias [*Bellenger et al.*, 2014; *Lloyd et al.*, 2011]. Ensemble averaging does not reduce these errors. Therefore, it is vital to explore other possibilities to improve numerical simulation of the Earth's climate.

Here we explore the *supermodeling* approach, in which multiple climate models are combined dynamically by exchange of information during the simulation. In a previous study, the state vector of each of several imperfect [*Lorenz*, 1963] models is nudged to the state vector of the other models, causing the different models in the ensemble to synchronize their evolution. The relative strengths of the nudging coefficients are optimized to bring the synchronized solution closer to the true evolution, in an attempt to match the attractor of the true Lorenz system [*van den Berge et al.*, 2011]. The supermodel with optimal coefficients is at least as good as the best model in the ensemble. The ensemble of interconnected models is in fact a single dynamical system, a "supermodel," that exploits the strengths of the individual models. The supermodeling approach requires that the models synchronize on a common solution, as this allows systematic errors to be compensated continuously.

The synchronization of chaotic systems connected through only a few variables is a common phenomenon in nonlinear dynamics [*Pecora et al.*, 1997]. The phenomenon has been demonstrated in quasigeostrophic models [*Duane and Tribbia*, 2001, 2004; *Hiemstra et al.*, 2012] and in an atmospheric general circulation model (AGCM) [*Lunkeit*, 2001]. Synchronization might similarly be established between coupled GCMs (CGCMs), bringing them into agreement. Indeed, numerical weather prediction models are required to synchronize with reality, based on sparse observations, in the data assimilation process [*Abarbanel et al.*, 2009; *Duane et al.*, 2006; *Yang et al.*, 2006]. In a supermodel as originally conceived [*Duane*, 2015; *van den Berge et al.*, 2011], models effectively assimilate data from one another. That synchronization among different models should facilitate synchronization/attractor matching between the resulting supermodel and truth is an example of a common relationship between internal and external synchronization [*Duane*, 2009, 2015].

Supermodeling requires real-time exchange of state information among the models. This is technically challenging when dealing with different models on different grids if we exchange the full state information. Here we generalize the related interactive ensemble construct to bypass these technical constraints. In a standard interactive ensemble, multiple realizations of an AGCM continuously interact with each other through coupling to a single ocean model that is driven by ensemble mean air-sea fluxes. This construct has been implemented to study aspects of ocean-atmosphere interaction as well as the mechanism of the El Niño–Southern Oscillation (ENSO) [*Kirtman and Shukla*, 2002]. In the SUperMOdel developed here, which we call "SUMO," two different AGCMs are coupled to one ocean model. An optimal combination of air-sea fluxes of the two AGCMs improves the simulation of the tropical Pacific. The current approach is effective only in this region, as only here strong ocean-atmosphere interaction enables the AGCMs to approximately synchronize [e.g., *Jansen et al*., 2009]; variance is lost when this does not occur. It is effective because AGCMs are deficient in representing the different air-sea fluxes to different degrees. Indeed, *Kirtman et al*. [2003] showed that by selecting heat and momentum fluxes from different AGCMs (instead of averaging them) in an interactive ensemble context, tropical Pacific climate could be improved.

In section 2 we explain the details of the model design and list observational products used, and in section 3 we demonstrate that SUMO has a more realistic mean state and ocean-atmosphere interaction as compared to the individual models. Sensitivity tests are discussed in section 4, and final conclusions are presented in section 5.

2. Models and Method

Our SUMO supermodel is based on the Community Earth System Models (COSMOS), which consists of fifth generation European Centre/Hamburg (ECHAM5) (AGCM) and Max Planck Institute Ocean Model (MPIOM) (ocean GCM), developed at Max-Planck-Institut für Meteorologie, Germany [*Jungclaus et al*., 2006]. We use two versions of the COSMOS model that differ only in the cumulus parameterization scheme: COSMOS(N) uses the *Nordeng* [1994] scheme and COSMOS(T) the *Tiedtke* [1989] scheme. Although both schemes favor convection in regions with maximum boundary layer moist static energy [*Möbis and Stevens*, 2012], in COSMOS they produce different climatologies over the tropical Pacific Ocean and both have substantial errors (section 3). We constructed SUMO by coupling the two versions of ECHAM5 to a single MPIOM version: Both atmosphere models calculate the air-sea fluxes based on the same sea surface temperature (SST), and the ocean receives a weighted average of the air-sea fluxes. A different combination of weights is used for each of the air-sea fluxes felt by the common ocean—energy, momentum, and freshwater (precipitation − evaporation). The sum of the weights over the two AGCMs equals unity, for each type of air-sea flux, maintaining conservation globally. The AGCMs employ T31 spectral resolution (i.e., ~3.75°) and 19 vertical levels; and the ocean employs a rotated curvilinear grid with an approximate 3° horizontal resolution and 40 vertical levels.

The Nelder-Mead [*Nelder and Mead*, 1965] machine learning algorithm, also known as the simplex method, was applied to optimize the weights for each of the air-sea fluxes. Its advantage is that it can find a local minimum of a cost function in multidimensional domain without having to compute gradients of the cost function. The cost function is defined as the root-mean-square difference between simulated and observed monthly mean SST climatology over the tropical Pacific region (160°E–90°W, 10°S–10°N) in the period 1948–1979. The model climatologies are computed from 30 year simulations by SUMO, and the observed is computed from the period 1948–1979. This region is chosen as there is approximate synchronization only over the tropical Pacific in our configuration (see Figure S1 in the supporting information). The cost function is based on monthly mean data so as to reproduce the mean seasonal cycle, in a crude attempt to match the attractor of the real climate. Starting from equal values, weights are adjusted iteratively according to the simplex method. Each evaluation of the cost function involves a spin-up for 10 years and a simulation for another 30 years to get a reasonable climatology. After optimization, requiring more than 300 model runs, the averaged SST root-mean-square error over the tropical Pacific region was reduced to 0.69°C from 2.82°C, 4.98°C, and 3.76°C in the COSMOS(N), COSMOS(T), and supermodel with equal weights, respectively (See Figure S2 for individual coupled model errors). The optimal weights are 0.43, 1.21, and 0.68 (0.57, −0.21, and 0.32) for momentum, heat, and freshwater, respectively, for the Nordeng (Tiedtke) version of ECHAM5; sensitivity to changes in the weights is discussed in section 4. The averaged correlation between the zonal wind stress anomalies of the two AGCMs over the tropical Pacific increased from 0.19 for equal weights to 0.36 after training, while the maximum correlation increased from 0.52 to 0.65. Note that the variability of AGCMs tends to

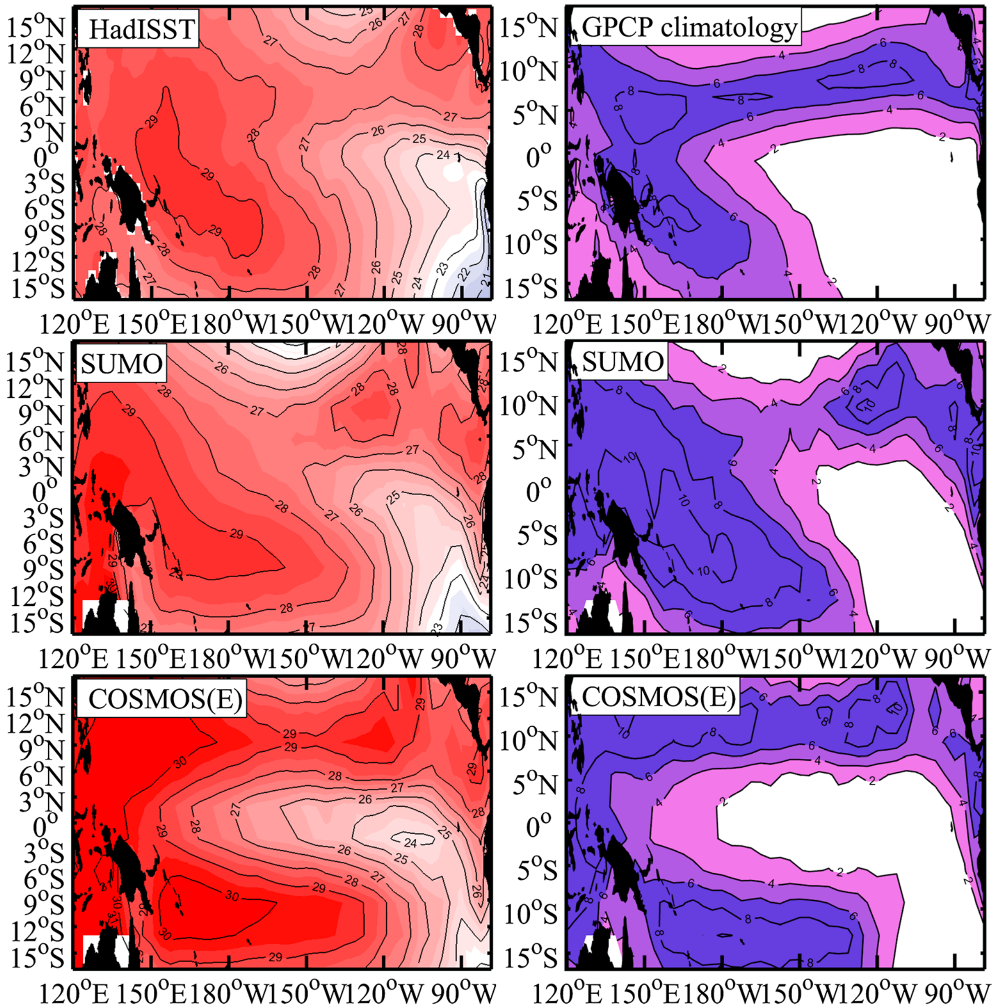

Figure 1. The (left column) climatological SST (scale in °C) and (right column) precipitation (scale in mm/d) in observations and models. The SST is from HadISST (1948–1979, the period used for the training set), and precipitation is from GPCP (1979–2012, due to availability of data). With improved representation of SST over the equator in SUMO, there is one ITCZ in SUMO.

cancel each other over nonsynchronized areas, thus reducing the ocean variability as well [*Kirtman et al.*, 2005] and causing a deterioration of model performance over the extratropical Pacific and Atlantic due to the loss of wind variability; hence, the global performance dropped in the midlatitudes. The optimal SUMO solution is discussed in more detail in the next section.

We use the following observational products. SST data are from Hadley Centre Sea Ice and Sea Surface Temperature (HadISST) [*Rayner et al.*, 2003]; precipitation from Global Precipitation Climatology Project (GPCP) [*Adler et al.*, 2003]; and surface wind stress and heat fluxes are from the National Centers for Environmental Prediction (NCEP) atmospheric reanalysis [*Kalnay et al.*, 1996]. Data for the period 1979–2012 are used to assess model performance, while SUMO is trained using SST observations for the independent period 1948–1979.

3. Mean State and Bias

The SUMO supermodel dramatically improves the simulation of the tropical Pacific mean state as compared to the COSMOS models, with the SST and precipitation agreeing better with observations (Figure 1). The cold tongue does not extend west of the International Date Line, indicating that SUMO maintains a west Pacific warm pool similar to observations. This is unlike the situation in either of the COSMOS models (Figure S2), which both simulate excessively strong cold tongues extending too far west. Consequently, this error remains pronounced in the mean of the two COSMOS models (Figure 1). SUMO improves quantities not directly optimized, with a

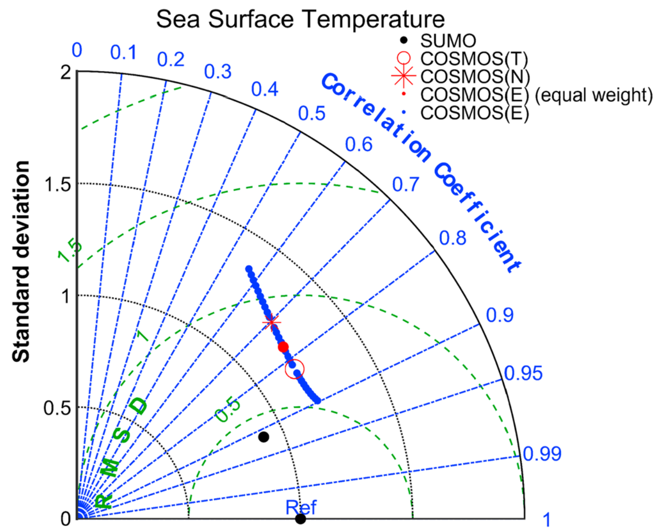

Figure 2. Taylor diagrams of the climatological SST pattern, showing both correlation with observations and standard deviation over the tropical Pacific region for COSMOS(T) (red circle), COSMOS(N) (red star), COSMOS(E) (red dot), traditional weighted ensembles (blue dots) with different weights (from −1 to 2), SUMO (black dot), and "observations," as given by NCEP Reanalysis (black dot marked "Ref").

more realistic simulation of the entire tropical circulation associated with the reduced SST bias. Most strikingly, SUMO largely mitigates the double ITCZ error found in both COSMOS models (Figures 1, S2 and S3) and in most climate models. Nevertheless, SUMO still exhibits substantial mean errors (e.g., it is too wet in South Pacific Convergence Zone).

No ex post facto weighted combination of COSMOS(N) and COSMOS(T) outputs has comparable performance to the SUMO result. In a Taylor diagram we compare the spatial correlation between model and observed SST, as well as the spatial standard deviations, for SUMO and the various weighted model combinations (Figure 2). SUMO has almost the same spatial standard deviation of SST as observed, unlike any of the models, with equal or unequal weights, and the correlation coefficient is higher. Similar results are found for precipitation (Figure S4). Thus, allowing the models to interact during run time yields better results than any average of their individual outputs.

Ocean-atmosphere interaction in the tropical Pacific is also greatly improved in the SUMO supermodel. To show this we use linear regression to assess two of the most important feedbacks in the equatorial Pacific: the Bjerknes positive feedback and the short-wave negative feedback [*Bellenger et al.*, 2014]. In the Bjerknes feedback, a positive (negative) central-eastern equatorial Pacific SST anomaly leads to a westerly (easterly) surface zonal wind anomaly over the central western Pacific, reinforcing the initial SST anomaly. Although this feedback is complex, linear regression is a common and effective method to estimate the strength of the resulting relation. SUMO is able to reproduce the observed dynamical relation very well, while both COSMOS(N) and COSMOS(T) underestimate the relation by around a factor of 2 (Figure 3a). The short-wave negative feedback, a positive (negative) SST anomaly in the central-eastern Pacific, leads to a reduction (increase) of incoming short-wave radiation, countering the initial SST anomaly. All three models strongly

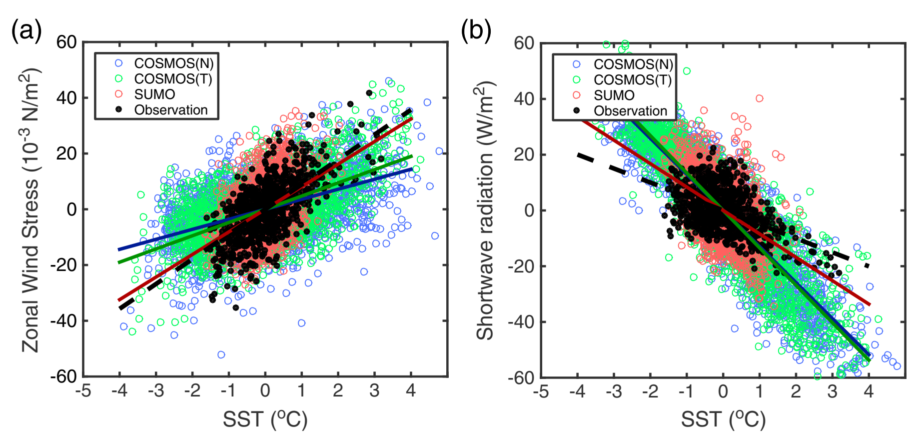

Figure 3. (a) The Bjerknes feedback, as described by the relation between the east Pacific SST anomaly (over 5°S–5°N, 150°W–90°W, Niño 3 region) and the remote wind stress over the west Pacific (5°S–5°N, 160°E–150°W, Niño 4 region); (b) the thermodynamic damping over the Niño 3 area, as described by the relation between the east Pacific SST anomaly and the short-wave radiation anomaly.

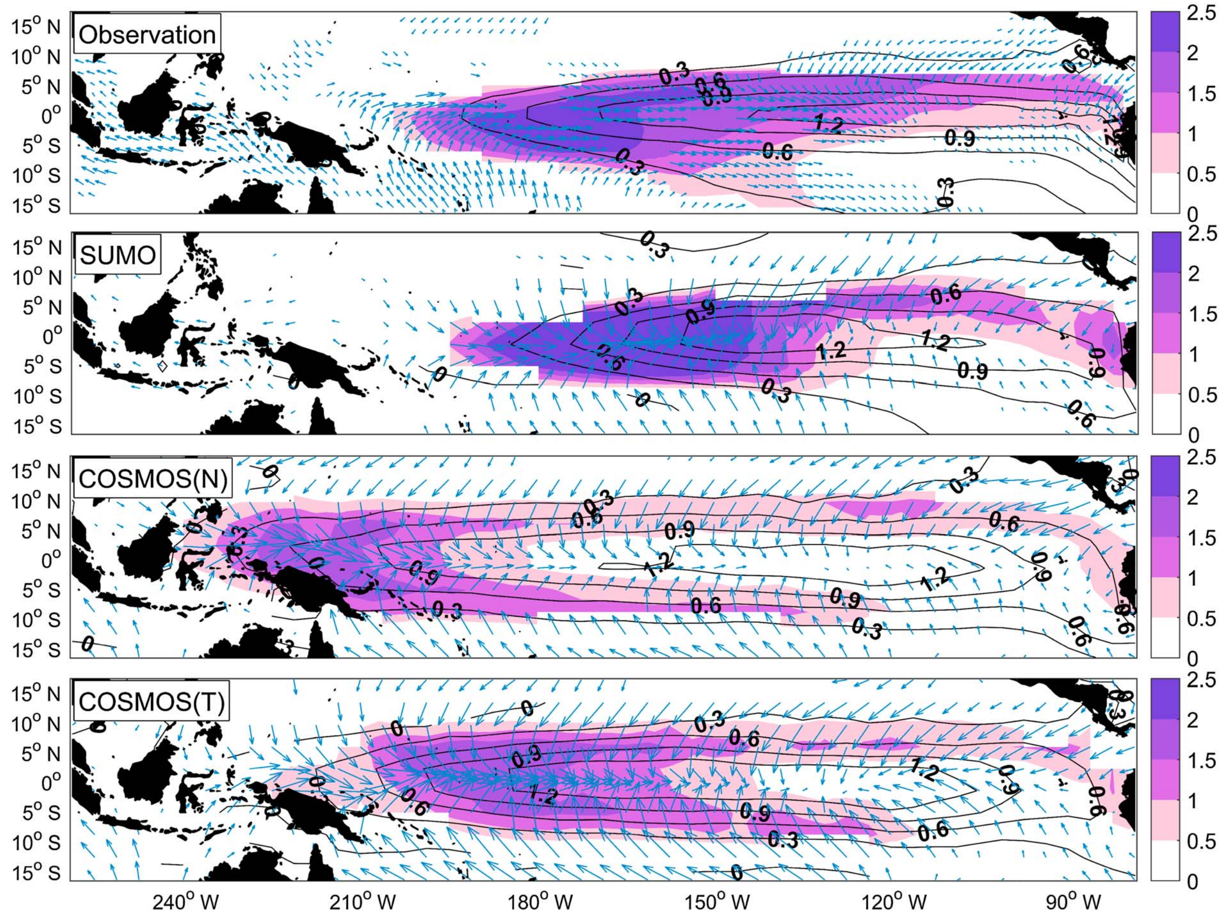

Figure 4. ENSO anomalies in SST (contours), precipitation (shading), and 10 m wind velocity (vectors). These patterns are obtained by linear regression against the SST anomaly over the Niño 3 region. (The three observables are taken from the same data set, NCEP Reanalysis 1, in order to maintain consistency).

overestimate this thermodynamic relation, but SUMO reproduces it best, with a more than 30% weaker relation than the two COSMOS models (Figure 3b).

The improvements in ocean-atmosphere interaction result from the compensation of errors in the individual model feedbacks, by optimal weighting of air-sea fluxes. Changes in the momentum flux, for fixed SST, from the weighted combination of the two models redefine the Bjerknes feedback in SUMO. The Tiedtke scheme is favored in SUMO with a weight of 0.57, as compared to 0.43 for the Nordeng scheme. For the short-wave feedback, it is the heat flux weights that determine the combination of feedback relations. The Nordeng scheme is favored in SUMO with a heat flux weight of 1.21, while the Tiedtke scheme is strongly disfavored with a weight of -0.21. The use of weights outside the range [0,1] in SUMO allows extrapolation beyond the range of the two separate models, so that even if the feedback relations for the separate models lie on the same side of the observed relation, the supermodel feedback can approach the observed relation more closely.

SUMO also improves the representation of tropical Pacific climate variability. ENSO-related SST, surface winds, and precipitation anomalies in SUMO are in closer agreement with observations than either of the COSMOS models (Figure 4). In observations and SUMO the anomalous SST is stronger in the east and hardly extends west of the International Date Line; whereas in COSMOS(N) and COSMOS(T) the anomalies extend across the whole equatorial Pacific. SUMO captures the strength of variability well: The Niño3 SST standard deviation is 0.88, 0.66, 1.78, and 1.65 in observations, SUMO, COSMOS(N), and COSMOS(T), respectively. As in observations, the ENSO-related westerly winds and precipitation anomalies in SUMO are situated over the central equatorial Pacific; they are situated much farther west in the COSMOS models. Nevertheless, SUMO exhibits clear deficiencies: it exhibits spurious SST anomalies in the North Tropical Pacific, and the ENSO-related precipitation and wind anomalies are too strong. The overall improvements in structure and

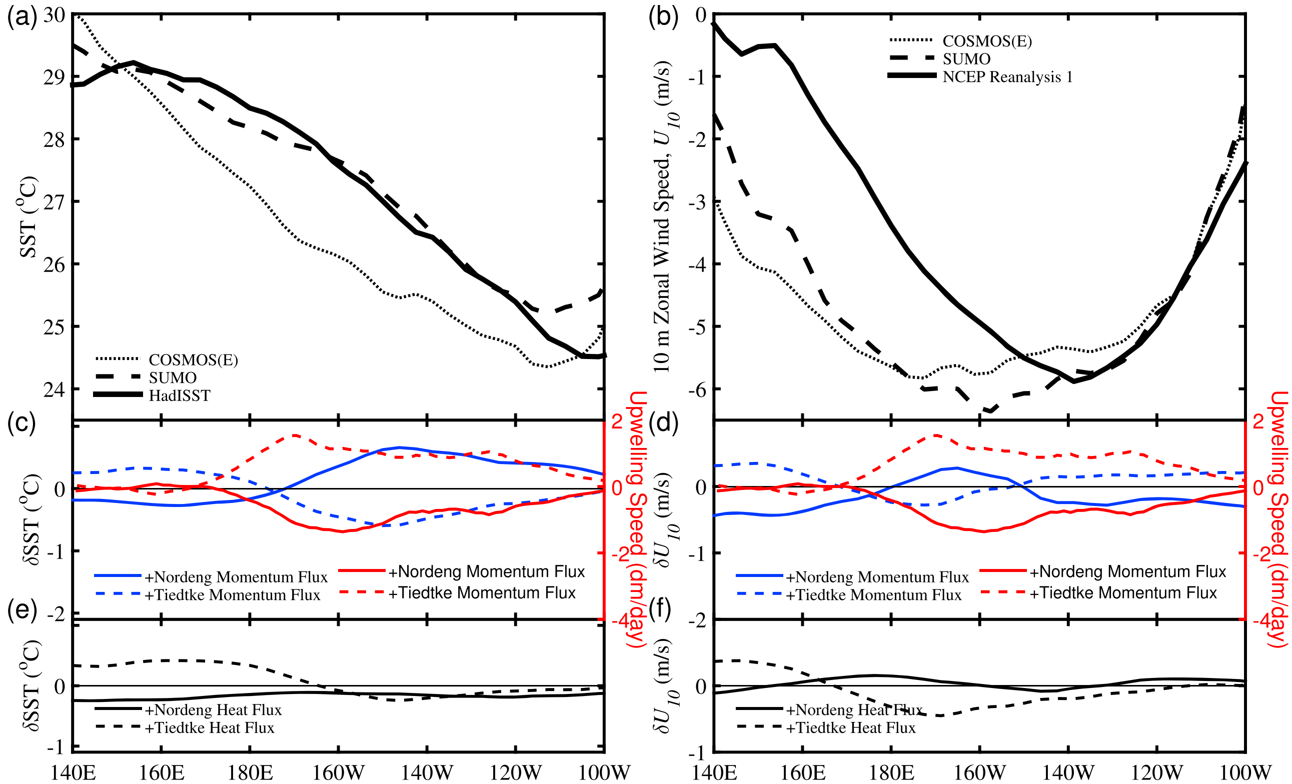

Figure 5. Equatorial (2oS-2oN) balances in control and perturbation experiments. Climatology (1948–1979) (a) SST and (b) zonal wind for COSMOS(E) (dotted), SUMO (dashed), and observations (solid; from HadISST and NCEP Reanalysis). (c, d) Differences in SST and in surface zonal wind between SUMO and the perturbed-momentum cases (more momentum flux from Nordeng atmosphere (blue solid) or from Tiedtke atmosphere (blue dashed)). The associated difference in ocean upwelling at 50 m deep is superposed (in red, in Figures 5c and 5d). (e, f) Differences in SST and in surface zonal wind between SUMO and the perturbed-heat cases (more heat flux from Nordeng atmosphere (solid) or from Tiedtke atmosphere (dashed)).

strength of ENSO-related variability are consistent with better simulation of the climatological state and ocean-atmosphere interaction in SUMO. We leave further analysis of simulated variability in supermodels to future studies employing models with increased resolution.

4. Sensitivity Tests

The mean state of the model is only a footprint of the nonlinear dynamical system and cannot provide the reason for the improved performance. The detailed mechanism through which supermodeling improves simulation of the tropical Pacific climate was examined by perturbing the weights of the air-sea fluxes. This shows not only the role played by each of the air-sea fluxes in ocean-atmosphere interaction but also the properties of the air-sea fluxes in individual AGCMs. Perturbing parameters is generally a good way to understand the form of the attractor and the mean state of a nonlinear system [*Nayfeh*, 2008; *Ostrovsky and Gorshkov*, 2000]. Experiments were conducted with the weights of heat, momentum, and mass fluxes perturbed separately by ±10%. SUMO's good simulation of the equatorial Pacific cold tongue is controlled by the weights of momentum and heat (Figures 5a, 5c, and 5e). Perturbing momentum fluxes impact oppositely the SST east and west of 170°W, with the largest effects around 150°W. The change of heat flux source mainly affects SST west of the International Date Line, with little effects to the east (Figure 5e). Perturbing the mass flux hardly impacts equatorial SST (not shown).

In COSMOS and SUMO the equatorial zonal wind stress is much stronger than the atmospheric reanalysis, and it is even stronger in the eastern Pacific in SUMO, despite the model's warmer SST (Figures 5a and 5b). In the perturbation experiments the changes in equatorial upwelling are consistent with the equatorial SST changes (Figure 5b). However, the changes in strength of the equatorial surface zonal wind alone cannot directly explain the changes in ocean surface upwelling, as mostly stronger (weaker) winds appear to drive weaker (stronger) upwelling in the east (Figure 5e). Rather increasing the momentum flux from Nordeng (Tiedtke) atmosphere drives changes in the off equatorial winds that drive a surface ocean circulation with increased (decreased) surface equatorial convergent flow; this weakens (strengthens) the oceanic shallow tropical cell causing warmer (cooler) equatorial SST, as well as introducing changes in the meridional SST gradient within 8° latitude of the equator (see Figure S5). Perturbing the surface heat flux has less impact on the surface wind stress, explaining the limited impact on equatorial eastern Pacific SST (Figures 5a and 5f).

5. Conclusions and Discussion

This work demonstrates that a climate supermodel (approximately synchronized suite of models trained for attractor matching with historical data) can be used to reduce well-known systematic error in CGCMs, even with incomplete synchronization of AGCMs. The tropical Pacific was targeted because approximate synchronization was found over that region. A set of weights was found by a simplex method that gives an optimal mean state in the tropical Pacific. In future work, the region of synchronization, and of supermodeling skill, will be extended by introducing upper atmospheric connections that would tend to bring the models into agreement in the midlatitudes.

The supermodeling method used here is a generalization of flux correction [*Sausen et al*., 1988] to dynamical corrections provided by another model, rather than temporally constant corrections to a single model based on observations. When supermodeling is effective, the models are synchronized, and thus the correction terms are small and do not violate substantially the dynamics of each model. This is in contrast to the effect of constant offset introduced by a flux correction. Additionally, only a single weight is required for each flux, rather than an entire field. Seasonally and spatially varying weights might lead to better results, as different convection schemes might represent convective behavior in different seasons and regions better. However, the task of robustly optimizing weights would be computationally more demanding. Better performance may also result if model is trained to reduce errors in SST and wind stress climatology, rather than only SST.

The benefit in the case examined was associated with the large improvement in the Bjerknes positive and short-wave negative feedbacks. It is in such higher-order quantities, where nonlinearities are important, that supermodeling is expected to improve over output averaging. These improvements are also consistent with an improved mean state. Perturbing the relative weights of the air-sea fluxes from the two atmospheres shows that equatorial SST over the east Pacific is sensitive to wind stress rather than heat flux, and altering the source of heat flux only has an impact over the west Pacific. The optimal combination gives improvement of equatorial Pacific dynamics and the ENSO-induced anomalies. It is in this manner that supermodeling can be hopefully used both to expeditiously improve climate prediction/projections and to give insight as to how to improve the separate models.

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