SUMO - Supermodeling by combining imperfect models

Workpackage 5: Year 2

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October 19, 2012
Comments of the authors

This report describes the work done in workpackage 5 of the SUMO project in year two, i.e. task 5.3, 5.4 and 5.5. The description of work says the following on the tasks:

Task 5.3 (month 13-20), construct a super climate model using a learning strategy: A first version of the super-climate model will be developed based on initial results of WP 1-4. The development will involve continued input from other WPs. Recommendations will be taken on the following:

- Whether to couple state variables or physical tendencies
- How to reduce of data dimensionality
- How to deal with fast atmospheric and slow ocean processes
- How to train the model on observational data

The supermodel will be trained over the period 1870-1980. [UiB, MASA, KNMI, RU, PIK]

Task 5.4 (month 19-24), test the super-climate model using independent data: Simulations will be made with the super climate model for the period 1980-2010 as well as a set of retrospective seasonal-to-decadal forecasts for the period 1980 till 2010. [UiB]

Task 5.5 (month 7-24), assess the super climate models constructed with connections chosen manually and using a learning strategy: The ability of the models to simulate the mean, variability, and global warming of climate over the independent period from 1980-2010 will be assessed. The skill of the trained super-model in predicting seasonal-to-decadal fluctuations (i.e., an initial condition and boundary value problem) will be quantified. Agreement and skill will be quantified using metrics developed in WP4 and compared to that of the individual models and their weighted average. [UiB, KNMI]

A framework of super climate model was built and able to couple N atmospheric models with one ocean model though the air-sea interface, thus only air-sea fluxes were coupled in this project year. Two methods suggested by the other WPs to train the models were applied and the performance was access by using Taylor diagram and comparing the 20 years performance over 1990-2009. We have performed seasonal predictions as a training method. However, a thorough assessment of the impact of the different approaches on seasonal prediction skill will be reported later; initial results will be presented at the annual meeting.
Summary

To test the super modeling strategy for climate prediction we coupled two atmospheric models with one ocean model. The atmospheric models differed in their convection scheme and climate-related parameters. As climate models show large sensitivity to convection schemes and parameterization, this approach may be a good basis for constructing a super model. We performed experiments with a small set of manually chosen coefficients and learning. The coupling strategy is able to synchronize atmospheric variability in the tropics, particularly over the western equatorial Pacific, and produce reasonable climate variability. Different coupling weights were shown to alter the simulated mean climate state. Some improvements were found that suggest a better strategy for choosing weighting coefficients could lead to a more improved simulation. Simulated variability was also affected by the different super modelling strategies, but little improvement was found. Some of the results were presented in deliverable D5.1, and they are not discussed further in this report.

1 Introduction

Scientists develop computer models of real, complex systems to increase understanding of their behaviour and make predictions. A prime example is the Earth’s climate. Complex climate models are used to compute the climate change in response to expected changes in the composition of the atmosphere due to man-made emissions. Years of research have improved the ability to simulate the climate of the recent past, but these models are still far from perfect. The model projections of the globally averaged temperature increase by the end of this century differ by as much as a factor of two, and differ completely in regard to projections for specific regions of the globe. The difference or uncertainty of model projections are attributed to several sources, e.g. time marching scheme, grid resolution and discretization as well as parameterization. Time marching scheme controls the stability of models and determines the strength of numerical dispersion and dissipation, which are commonly arisen when the time step and grid resolution are not fine enough to convey the physical signals. The grid resolution and discretization define dynamic and physics that can be resolved by models. For instance, the heat flux and sea surface temperature of Kuroshio-Oyashio Extension (KOE) are dominated by the activities of eddies [1] and thus the surface hear flux exchanges cannot be resolved properly if not using eddy-permitting (quarter degree horizontally) or eddy-resolving (one tenth degree) ocean models. Therefore the incorrect heat flux over KOE has to be tuned locally in the models with horizontal grid resolution larger than quarter degree. Parameterization is mainly used to represent the state of the fast or small scale processes which cannot be resolved by the resolution used. However, it is impossible for parameterization to cover all the missing process, especially one not discovered yet. It has implication that the perfect model is unlikely to be built by improving the performance of single model. The current practice to reduce model uncertainty is to average the predictions of the separate models. Here we take a novel approach and build a super model (i.e., an optimal
combination of several models): We couple two atmosphere GCMs (AGCM, ECHAM) and one ocean GCM (OGCM, MPIOM). The two AGCMs receive identical boundary conditions from the OGCM, while the OGCM is driven by a weighted flux combination from the AGCMs. The remainder of this report is organized as follows: Section 2 provides the descriptions of data and models we applied, as well as the climate-related parameters; Section 3 presents the results of our numerical experiments, including the performance of manual chosen weighted SUMO and the SUMO after learning; and lastly Section 4 offers conclusions.

2 Data and Model Descriptions

2.1 Data

Observables here are from NCEP Reanalysis data [2] provided by the NOAA/OAR/ESRL PSD, Boulder, Colorado, USA, from their Web site at http://www.esrl.noaa.gov/psd/. The surface fluxes were used in order to build comparison of the air-sea interface we employed to couple two AGCMs with one OGCM. The observables were precipitation, 10 m zonal and meridional wind velocity, 2m air temperature and sea surface temperature. We also considered the top of atmosphere imbalance of heat flux to identify the reality of our models. The duration of the data set is from 1948-present. We used 20 years data (1990-2009) to access the performance of models and 61 years data (1950-2011) to access the characteristics of forecast.

2.2 Climate Model

In this work we use the Community Earth System Model (COSMOS) as the basis for a super climate model. COSMOS, developed at Max-Planck-Institut für Meteorologie (Germany), is a framework to develop and apply coupled atmosphere/ocean/land models for Earth system research as shown in Figure 1. The COSMOS software package allows to build different models including the physical climate model ECHAM5/MPIOM (the European Centre for Medium-Range Weather Forecasts (ECMWF) Hamburg atmospheric general circulation model version 5), and the carbon cycle-climate model ECHAM5-JSBACH/MPIOM-HAMOCC. COSMOS uses the PRISM software for infrastructure. For more information see http://cosmos.enes.org.

The numerical experiments were performed with an atmospheric spectral resolution of T31 and 19 vertical layers (T31L19), which corresponds to approximately 3.75 degrees horizontally; the ocean horizontal resolution was approximately three degrees and 40 vertical layers (GR30L40). This relatively coarse model resolution was adopted to allow the construction of a larger super-model and permit extensive experimentation.

2.3 Model Uncertainty and Diversity

An important issue for super-modeling is increasing the diversity of models. Namely, even though the models are imperfect and may introduce great uncertainty, the diversity
of models is necessary to have a projection covering the possible future; the challenge is keep an accurate level of the unknown uncertainty. One straightforward method to increase model diversity is to couple two different models developed by different group and with different structures. However, there are many technical issues that have to be surmounted to couple two different climate models, because normally there is no general interface among component models. Two methods to increase model diversity are used here. One is changing the convection scheme in AGCM; another is perturbing the climate-related parameters in the atmospheric model to create different parallel worlds [3, 4]. We do not consider changes in oceanic parameters. The detail are now described.

2.4 Convection Schemes

Convection schemes in AGCM are mainly cloud-related and usually show considerable sensitivities of model results [5]. Convection may arise dynamically or thermally or both, and the entrainment and detrainment in one cloud may not happen in the same grids. Furthermore, these processes occur on very small scales. Due to insufficient computer power atmospheric convection is a parameterized process in global or even regional models, i.e., it is based on several diagnostic equations to estimate the fast process and heavily influenced by the large-scale fields or background circulation. Parameterizations require a closure assumption that must hold at each column. Various closure assumptions have been implemented, and these give rise to large model sensitivity.

ECHAM5 adopts convective parameterization schemes which is based on the Tiedtke scheme [6], but implement different closure strategy. There are three different choices in ECHAM5: original Tiedtke closure, hybrid closure and Nordeng scheme [7]. The
latest one is the default scheme. The original Tiedtke scheme uses large-scale moisture convergence, the conservation of temperature and specific humidity is considered. The Nordeng scheme uses cloud base mass flux related to the available potential energy (CAPE) relaxation closure. Unfortunately, the parameter tuned version of ECHAM5 was only available for the Nordeng scheme. Thus, the performance of the model with the other convection schemes may be worse, mainly because no parameter tuning was applied. This should not be seen as concern in the super-model concept, which assumes imperfect models.

2.5 Climate-Related Parameters

To create a large ensemble of imperfect models, several climate-related atmospheric parameters were selected and varied within the range listed in Table 1. The ranges are suggested by Haeter et al. [3] and Klocke et al. [8], and allow realistic climate simulations for Nordeng scheme. Figure 2 shows the physical region which is influenced by the parameters and a short statements were listed below to describe their impacts.

- Cloud mass-flux above level of non-buoyancy
  – affecting cloud water content and size
  – smaller values repress evaporation of clouds and sustain clouds, and vice versa for large values.

- Entrainment rate for shallow convection
  – affecting cloud water content and size
  – large values can lead to an increase in cloud water content and larger cover of low level clouds.

- Entrainment rate for penetrative convection
  – affecting cloud water content and size
  – large values can lead to an increase in cloud water content and larger cover of high penetrating clouds.

- Conversion rate from cloud water to rain
  – determining the conversion efficiency of convective cloud water to precipitation.

- Inhomogeneity of liquid clouds (controlling the microphysical properties of clouds)

- Inhomogeneity of ice clouds (controlling the microphysical properties of clouds)

- Correction to asymmetry parameter for ice cloud (controlling the microphysical properties of clouds)
Figure 2: Schematic diagram of the parameters that introduce the climate uncertainty and might be tuned in this study. Stratiform liquid and ice clouds, and shallow and deep convective clouds are represented. The dashed gray line indicates the top of atmospheric boundary layer and the solid grey line the tropospheric temperatures. The parameters are a) convective cloud mass-flux above the level of non-buoyancy, b) shallow convective cloud lateral entrainment rate, c) deep convective cloud lateral entrainment rate, d) convective cloud water conversion rate to rain, e) liquid cloud homogeneity, f) liquid cloud water conversion rate to rain, g) ice cloud homogeneity, and h) ice particle fall velocity [4].

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Range</th>
<th>Default Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cloud mass-flux above level of non-buoyancy</td>
<td>0.1-0.333</td>
<td>0.3</td>
<td>$m^{-1}$</td>
</tr>
<tr>
<td>Entrainment rate for shallow convection</td>
<td>$3 \cdot 10^{-4} - 1 \cdot 10^{-3}$</td>
<td>$3 \cdot 10^{-4}$</td>
<td>$m^{-1}$</td>
</tr>
<tr>
<td>Entrainment rate for penetrative convection</td>
<td>$3 \cdot 10^{-5} - 5 \cdot 10^{-4}$</td>
<td>$1 \cdot 10^{4}$</td>
<td>$s^{-1}$</td>
</tr>
<tr>
<td>Conversion rate from cloud water to rain</td>
<td>0.0001-0.005</td>
<td>0.0004</td>
<td></td>
</tr>
<tr>
<td>Inhomogeneity of liquid clouds</td>
<td>0.65-1</td>
<td>0.7</td>
<td></td>
</tr>
<tr>
<td>Inhomogeneity of ice clouds</td>
<td>0.65-1</td>
<td>0.8</td>
<td></td>
</tr>
<tr>
<td>Correction to asymmetry parameter for ice cloud</td>
<td>0.75-1</td>
<td>0.85</td>
<td></td>
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</table>
3 Experiments and Results

The experiments were performed based on the schematic diagram shown in Figure 3. Four sets of experiments were performed in this project year and applied different approaches to have the weight coefficients of the surface fluxes from the AGCMs to the OGCM. The first set is the SUMO with manual chosen weights. The change of the weights is linear. In the second experiment the tendency error between model results and observations were used to calculate the weights at each grid point. The third experiments we tried coupling several parameter perturbed atmosphere models together to perform a SUMO with small bias in climatology. The fourth set is using Nelder Mead simplex algorithm to train the weights with minimum bias.

![Figure 3: Schematic diagram for SUMO. Several atmospheric models (ECHAM5) were coupled to one ocean model (MPIOM) through exchanging surface flux. The diversity of the atmospheric models was arisen by using different convection schemes and/or different climate-related parameters.](image)

3.1 Manual chosen weights

Three experiments were accomplished to assess the impact of different weighting coefficients of the coupling fields. They are SUMO(T75N25), SUMO(T50N50) and SUMO(T25N75). The symbol T indicates the Tiedtke scheme was used in the AGCM, and N indicates the Nordeng scheme. The number indicates the percentage of the weighting coefficient of the coupling fields. The coefficients changes are linear, but one may expect a nonlinear impact on the simulated phenomena.

Partial synchronization was found in the results of SUMO(T50N50) shown in Figure 4.
when the variability of the atmospheric component models was compared. The temperature anomaly over tropical column was highly synchronized as shown in Figure 4(a). This implies that the tropical tropospheric temperature is dominated by the convective response to ocean variability over tropical zone, for both of moisture convergence (Tiedtke) and CAPE relaxation closure (Nordeng). The correlation of temperature anomaly drops quickly outside the tropical zone, and suggests the synchronization of the atmospheric dynamics might be weak outside the tropical zone, which can be further seen in Figure 4(b). Only the surface zonal wind stress anomaly of the western tropical Pacific was synchronized through sharing identical fluxes from the OGCM. This is consistent with many previous studies showing the tight coupling between ocean and atmosphere over the tropical Pacific. It also indicates that the 2D coupling is not able to significantly synchronize models away from this region.

Figure 4: Correlation of zonal-averaged temperature anomaly (a) and zonal wind stress anomaly (b) between ECHAM(Nordeng) and ECHAM(Tiedtke) of SUMO. Non-significant correlations were set to be blank. High correlation can be found in tropical region, especially the western Pacific tropic.

The global averaged SST shows little differences among the simulated biases in the extra-tropic (Figure 5), and is quite similar to that of the uncoupled models (see deliverable D5.1). The main difference of extra-tropics is the cold anomaly is strong at the California Current in both SUMO(T75N25) and SUMO(T25N75), which suggests the California Current or the equatorward wind stress is strong, thus more cold water is transported from the north and upwelling is strengthened.

The SST of SUMO(T50N50) has the warmest tropical temperature of these three experiments. Adjusting the weighted coefficients entirely toward to one specific scheme fails to produce a better simulations of the tropical climatology, as there is a colder bias found in the other two experiments, SUMO(T75N25) and SUMO(T25N75). This has implication that the one degree of freedom (the weighting coefficient of coupling fields) is not enough to have a better approach. Varying manual chosen coefficients among coupling fields should increase the degrees of freedom, and in the future we will test if this may lead to an improved simulation.
Figure 5: (a) The difference of SUMO(T75N25) and the HadISST; (b) the difference of SUMO(T50N50) and the HadISST; (d) the difference of SUMO(T25N75) and the HadISST. Over the equatorial Pacific only SUMO(T50N50) simulated nearly zero bias. The SUMO(T75N25) and SUMO(T25N75) both simulated strong cold bias, implying the performance to the weighting coefficients is nonlinear.
Here we use Taylor diagrams [9] to compare the similarity among models and observations, and objectively assess model improvements. Three non-dimensional statistics are presented in the Taylor diagram. They are the ratio of the variances and observations, the correlation, and the root mean square distance (or error) between model results and observations. The plot is constructed based on the Law of Cosines. The observed field is represented by a point at unit distance from the origin along the abscissa. All other points, which represent simulated fields, are positioned such that the ratio of the variances are the radial distance from the origin, the correlation is the cosine of the azimuthal angle, and r.m.s. distance is the distance to the observed point. Thus a good agreement is found when the distance to the point representing the observed field is relatively short.

We assess the model performance for six observables, all related to ocean-atmosphere interaction and hence important to our coupling strategy (Figure 6). All the SUMOs shows better performance than the COSMOS on surface and 2 m air temperature. However, the performance of zonal winds was drifted apart which implies the behavior of convection scheme is very different when they receiving identical SST from ocean.

3.2 Learning from Tendency Error

Bansnarkov & Kocarev (2012) suggested an approach that can reduce the tendency error by the linear combination of models. Namely the weighting coefficients can be determined by the tendency error of model results and observations. A numerical experiment was performed to determine these coefficients. We restored the SST of model to observation for the period 1950-2011. This approach leads to upper ocean conditions close to observations in the Tropical Pacific (not shown), thus providing sixty two years of data for initializing seasonal predictions. Then we performed half-year prediction runs (from January and July respectively) to provide model SST tendencies. Tendency errors were computed using observed SST changes. These were used to compute the spatial weighting coefficients (Fig. 7).

Compared to the SST bias of SUMO(T50N50), i.e., the equal weighted SUMO (Figure 5b), some minor improvements can be found over Tropical Pacific and Southern Ocean (Figure 8). The performance of global SST, 2 m air temperature, and 10m winds remains similar to that of the models constructed with manually chosen weights, but performance seems degraded for sensible and latent heatflux (Figure 9).
Figure 6: Taylor diagram for six surface observables (surface temperature, 2 m air temperature, zonal, meridional wind speed, sensible and latent heat) over global region.
Figure 7: Weight coefficients determined by reducing the tendency error. The weights were nudging to 0.5 for high latitude region.

Figure 8: The difference of spatial weighted SUMO (SWSUMO) and equal weighted SUMO (EWSUMO or SUMO(T50N50)). Improvements were found over northeast Pacific, in which the cold bias indicates the reducing warm bias of EWSUMO in Figure 5(b), and over southern ocean, in which the warm bias indicates the reducing cold bias of EWSUMO.
Figure 9: Global performance of spatial weighted SUMO. A good performance was found in the temperature fields. However, the zonal wind speed of both AGCMs in the SUMO shows bad performance.
3.3 Learning from Climatology

Based on Section 2.3.2, we perturbed the seven climate-related parameters using both Tiedtke and Nordeng schemes to have a series of new atmosphere component models. The performance of each component model was assessed separately in coupled model simulations (only one AGCM and one OGCM). Perturbing the climate-related parameters introduces a lot of model diversity (Figure 10). However, the convection scheme has much stronger impact on the variance ratio of the surface temperature and turbulent heat fluxes than perturbing the parameters alone (Figure 10). However, the variability (or the variance ratio) of zonal wind is quite similar independent of the convection scheme used. Switching the convection scheme or altering the climate-related parameters primarily impacts the correlation of simulated zonal wind with the NCEP/NCAR reanalysis.

We selected five AGCMs that have approximately zero global temperature bias in their multi-model mean. These were coupled to the OGCM to produce a SUMO with five parameter perturbed AGCMs, referred to as SUMO(PP). The simulated global mean temperature bias is only 0.06°C that is better than that of COSMOS(T), 1.04°C, and of COSMOS(N), -0.21°C. This shows the potential to build a super model to accomplish certain (temperature) target. In terms of spatial patterns, the SUMO improves on the five uncoupled models for surface temperature, but the agreement with the NCEP-NCAR for 10m-winds and turbulent fluxes does not improvement (Figure 11).
Figure 10: Taylor diagram for 200 experiments, in which the parameters listed in Table 1 were perturbed. Two groups can be found in SST and 2 m air temperature. This is mainly attributed to the convection scheme. The standard deviation of the temperature of Nordeng scheme is about 1.3 and of Tiedtke as well as hybrid scheme is about 1.5.
Figure 11: Taylor diagram for the model results of the AGCMs of the five COSMOS models and that of the AGCMs coupled to one OGCM.
3.4 Training

Calculating tendency error is a fast and computationally cheap method to determine the weighting of imperfect models, as compared to online training. However, it can only be used for observations that are directly related to the global coupling fields (i.e., SST is related to the surface fluxes, and so tendency errors in SST can be corrected by weighting the fluxes). To overcome this limitation, we intend to train a super model based on the Nelder Mead simplex algorithm [10], which was suggested by WP2 and can converge to local minima without using tendencies. The fundamental concept of the Nelder Mead simplex algorithm applies three different strategies (reflection, expansion and constriction) to determine optimal weighting coefficients.

4 Conclusions

In order to summarise the results of all the simulations, we compute a performance index [11] that quantifies the model error considering a number of observed quantities together. The normalized error variance is defined as follows:

\[
E^2 = \frac{\sum (s_{vnm} - o_{vn})^2}{\sigma_v^2}
\]  

(1)

where \(s_{vnm}\) is the climatology of model variable \(v\), model \(m\), and grid point \(n\); \(o_{vn}\) is the corresponding observed climatology; \(\sigma_v^2\) is the variance of the observations. The performance index is formed by taking mean over the normalized error variances of all observables. A smaller value represents a model overall closer to observations. The seven observables related to ocean-atmosphere coupling were considered here. The results were shown in Figure 12. In this work the performance were normalized by the value of the metric of COSMOS(T) in order to have the indices centered around unity. A model with a value less (greater) than unity is a better (poorer) model than COSMOS(T).

![Figure 12: Performance index over seven observables and the ensemble mean of the indexes. Lower is better.](image-url)
In general, when considering latent and sensible heat flux and 2m and surface temperature, and 10m zonal and meridional wind the best model is the well tuned COSMOS(N) (Figure 12). It has good performance in heat flux, temperature and surface wind velocities. It is also the best model when considering all these quantities together.

The performance metric is very sensitive to the inclusion of convective precipitation, which is heavily influenced by the convection scheme and cloud parameters. COSMOS(N) prefers precipitating over the ocean in the tropical region, whereas in the NCEP/NCAR reanalysis there is preference for precipitating over land [4]. The large sensitivity to precipitation means that the performance index determined by the seven observables is dominated by the convective precipitation, because it contributes most of the uncertainty. It should be noted that the convective precipitation in the NCEP/NCAR reanalysis is essentially a product of the model. The results are only included to demonstrate the large spread among the performance of the different super models in terms of their simulation of convective precipitation.

References


[7] T.E. Nordeng and European Centre for Medium-Range Weather Forecasts. *Extended Versions of the Convective Parametrization Scheme at ECMWF and Their*


