A New Method for Exploring Coupled Land–Atmosphere Dynamics

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ABSTRACT

This paper proposes a new method for investigating coupled land–atmosphere interactions. The method is to apply an empirical correction technique to distinct components of a model and then examine differences between forecasts of the empirically corrected models. The correction technique is based on adding a time-dependent term to the tendency equations that subtracts the estimated tendency error at every time step. This methodology can be interpreted more generally as a series of data assimilation experiments in which only certain components of a coupled model are assimilated at a time. The correction is applied to a state-of-the-art coupled land–atmosphere model in three different ways, namely, to the atmosphere only, to the land only, and to the land and atmosphere simultaneously. The land–atmosphere interactions are inferred from monthly-mean differences between experiments. The results suggest that the land–atmosphere coupling in midlatitudes can be understood from straightforward water balance considerations, whereas the coupling in the deep tropics involves a more complicated change in regional circulation. Specifically, in midlatitudes, moisture injected into the soil is transferred to the atmosphere directly above, which in turn advects downstream and subsequently moistens the atmosphere in the downwind regions to produce positive precipitation anomalies. In the deep tropics, the regional circulation, including precipitation, is sensitive to perturbations and has no obvious relation to corrections in the atmosphere or land. The similarity of biases among different models suggests that the conclusions and methodology may be relevant to other models.

1. Introduction

General circulation models (GCMs) are imperfect, owing to their finite resolution and parameterization of incompletely understood physical processes. Consequently, even with perfect initial conditions, GCM forecasts exhibit systematic errors. These errors degrade the GCM’s simulation of the mean climate and may impede its utility as a forecasting tool. The fact that systematic errors have persisted despite sustained efforts to eliminate them by world-class operational forecasting centers attests to the difficulty of the problem. Complicating the problem is the change in behavior, and often an increase in sensitivity, that occurs when component models of the climate system (e.g., atmosphere, land, and ocean) are coupled.

A practical way to make progress is to reduce the systematic biases in a model by applying a statistical correction. Several strategies for empirically correcting models have been proposed, such as adjusting the fluxes between component models (e.g., Manabe et al. 1991), passing anomalies rather than total fields between components (e.g., Kirtman et al. 1997), or nudging state variables in component models based upon tendency errors (e.g., Leith 1978; DelSole and Hou 1999). Recently, DelSole et al. (2008) expanded the latter approach by estimating and applying correction terms simultaneously in both the atmosphere and the land models. Applying corrections to both atmosphere and land has distinct advantages compared to correcting just
the atmospheric component. For instance, Dirmeyer (2000) and Douville (2003) showed the positive effect of more realistic land surface states on seasonal climate prediction. Dirmeyer (2003) showed that large systematic errors in the land surface state—namely, soil moisture—can reduce sensitivity and feedbacks to climate anomalies. Koster and Suarez (2003) and Koster et al. (2004a) found that the quality and consistency of the initial state of the land surface could affect forecast skill for months. Dirmeyer and Zhao (2004) showed that correcting the flux of water and energy from the atmosphere to land subsequently reduced errors in atmospheric state variables and fluxes.

One limitation of statistical forecast correction is that the correction does not, in itself, give insight into the source of the errors. However, empirical correction methods can be useful for diagnosing the source of the errors. For example, Schubert and Chang (1996) proposed fitting tendency errors to a linear combination of tendencies produced by individual physical parameterizations. The resulting best fit model effectively partitions error among the physical parameterizations and thereby identifies parameterizations that are linearly related to the tendency errors. Despite its great potential, this method has yet to be used systematically by model developers to improve dynamical forecast models.

We suggest in this paper that empirical correction methods also can be used to gain insight into the dynamics of forecast models. Specifically, instead of empirically correcting all components simultaneously and being satisfied with the reduced forecast error, we suggest applying the correction also to a subset of components. For instance, one could correct only the land component while leaving the atmosphere uncorrected. Having constructed two distinct correction runs, we can then compare the statistics of the two runs to identify how the correction terms modify the forecasts. We believe that comparing corrected runs to uncorrected runs would be especially enlightening. Because the two runs differ only in the forcing, familiar methods for understanding the response of a dynamical model to anomalous forcing can be applied. The new element here is that the imposed forcing is motivated by the short-term forecast errors of the model. The hope is that by perturbing the model in a manner designed to reduce forecast errors, the response may give insight into the dynamics of the errors, which in turn may give insight into how model errors could be reduced.

In principle, different models may have different error dynamics. However, recent studies reveal that different coupled land–atmosphere models produce similar biases (Koster et al. 2004b), suggesting that insight gained from one model might be useful to other models. To illustrate this similarity further, we show in Fig. 1 the July–August temperature and humidity biases of nine different coupled land–atmosphere models, as estimated from the Global Land–Atmosphere Coupling Experiment (GLACE). The figure reveals that seven out of nine models have cold biases in the Alaska–northern Canada region, all of the models have warm biases in the U.S. Great Plains and the Middle East, and five out of nine models have dry biases in central Africa. The consistency of the errors across models is quantified in Fig. 2, which shows the mean forecast error over all models, divided by the standard deviation of the mean forecast errors over all models; large absolute values of this “signal-to-noise ratio” indicate regions where errors are consistent among models. The figure confirms that strong warm biases occur in the Great Plains and the Middle East but also reveals that wet biases occur in regions of significant topographic variability. Thus, an effective correction strategy found for one model has the potential to be effective in other models.

Our methodology for exploring the dynamics of land–atmosphere coupling is reviewed in the next section. The datasets and models used in this study also are reviewed in the next section. The results of applying this methodology to a coupled land–atmosphere model are discussed in section 3, and we close with a summary and discussion of our results.

2. Methodology, data, and model

We applied the empirical correction approach of DelSole et al. (2008). Briefly, the model is integrated for 24 h starting from each day in June during the period 1982–91. Then, the forecast errors at 6, 12, 18, and 24 h are fitted to a linear function of lead time, and the resulting slope is adopted as an estimate of the instantaneous tendency error. This fitting procedure is applied to each grid point individually and independently. The model is then integrated again starting from the same initial condition but with the estimated tendency error subtracted at each time step. The result is called a “nudged” forecast, and the extra terms in the tendency equations are called “nudging parameters.” The nudged forecast is a kind of data assimilation in which the model is nudged toward observation-based data. The end of the 24-h nudged forecast is then used as the initial condition for the next iteration of this cycle. Further details of this procedure can be found in DelSole et al. (2008).

We used the Center for Ocean–Land–Atmosphere Studies atmospheric general circulation model, version 3.2 (COLA AGCM V3.2) at a spectral resolution of T62 (1.875 longitude and latitude on the corresponding
Gaussian grid) with 28 vertical levels. The main features of this model are reviewed in Misra et al. (2007). Aside from the dynamical core, virtually every major component of this model differs from the earlier version (V2.2; Kinter et al. 1997). The AGCM is coupled to an updated version of the Simplified Simple Biosphere model (SSiB; Xue et al. 1991, 1996; based on Dirmeyer and Zeng 1999). We refer to the coupled system simply as the GCM. Among the major differences, we mention that the land model in V3.2 predicts soil temperature and wetness in six layers (instead of three), with four embedded within the root zone. Relative to the older model, the increased vertical resolution of the soil produced better evapotranspiration and vertical profiles of soil moisture. The sea surface temperature is specified from the weekly analysis of Smith and Reynolds (2004).

As shown in DelSole et al. (2008), the empirical correction substantially reduces climate drift but does not eliminate it completely. Therefore, to avoid contamination from climate drift, we restrict attention to the first month of forecasts; that is, we consider only forecasts starting on 1 June and ending on 30 June. The dataset used to validate the atmospheric forecasts is the reanalysis product by National Centers for Environmental Prediction (NCEP; Kalnay et al. 1996). The dataset—including soil moisture, soil temperature, and snow cover—used to validate the land forecasts is the new Global Offline Land surface Dataset (GOLD; Dirmeyer and Tan 2001). To avoid errors arising from the interpolation of atmospheric data to the model grid, we extracted the reanalysis data in spectral form on the same 28 sigma levels as used in the data assimilation system. Furthermore, the COLA V3.2 model was run at exactly the same resolution as the NCEP reanalysis model—namely, T62L28—with identical topography. Furthermore, an updated GOLD dataset using the same land model as the COLA V3.2 was generated specifically for this project to ensure consistency between the offline and COLA V3.2 land surface models and to provide data on six-hourly intervals.

In the atmospheric model, only tropospheric temperature (t0), zonal velocity (u0), and meridional velocity (v0) are corrected. Correction of water vapor
concentration had little effect on the forecast and was deemed inappropriate given the questionable accuracy of this variable in the reanalysis. Surface pressure was not corrected because of technical difficulties arising from its being integrated in spectral space, in contrast to the other variables that are integrated in grid space. In the land model, soil temperature (st) and soil wetness (sw) are corrected at all six soil layers.

As discussed in DelSole et al. (2008), a wide variety of experiments schemes were performed. The present paper focuses only on four types of runs with nudging based on tendency errors: control runs with no nudging, runs with simultaneous land–atmosphere nudging (A + L), runs with land-only nudging (L), and runs with atmosphere-only nudging (A). These runs correspond to the a, j, k, and l runs, respectively, listed in Table 1 of DelSole et al. (2008), which also has further details of the numerical experiments.

Results for atmospheric variables are shown primarily for the lowest level ($\sigma = 0.99$) and for $\sigma = 0.17$, corresponding to approximately 170 hPa. Results for land variables are shown for the second model level, which has depths ranging from 4 to 14 cm, depending on vegetation. Results for other soil layers mimic those on the second soil level, except for a general decrease in error amplitude with depth.

3. Results

We first consider how well the empirical correction nudges the forecast toward verification. The root-mean-square difference between the nudged forecast and verification is shown in Fig. 3. (The result for $u_0$ is virtually identical to $v_0$ and hence is not shown.) The figures show that nudging both land and atmosphere substantially reduces the differences, as expected. In effect, the nudging is a data assimilation procedure, except that it assimilates an analysis product rather than observations. The figure reveals that land nudging has little effect on the atmosphere at upper levels, and that atmospheric nudging has only marginal effect on the soil wetness errors. In contrast, nudging of near-surface temperature of one component tends to reduce temperature errors in the other component.

The average nudging parameters for June, when both atmosphere and land are nudged, are shown in Fig. 4. The parameters derived from nudging land-only or atmosphere-only are very similar (not shown). We see that the nudging acts to cool the lower atmosphere and...
warm the upper atmosphere, thereby counteracting the known cold bias aloft and the warm bias at low levels. The nudging also tends to inject water into the soil, except in Greenland and parts of the Himalayas where it tends to remove water. The nudging of soil temperature has more complex spatial structure, although it tends to cool where it also injects water. Therefore, the soil wetness and soil temperature nudging tend to oppose warm-dry biases in the land component. Interestingly, the nudging parameters for soil temperature and low-level atmospheric temperature do not have the same sign everywhere (cf. Figs. 4a and 4c). The fact that the structure of the nudging parameters (shown in Fig. 4) differs from that of the COLA model errors (shown in Fig. 1) reflects the difference between short-term and long-term forecast errors, as well as differences in model versions and verification periods. The nudging of low-level winds has complex spatial structure. However, the mean square error of forecasts without wind nudging is virtually identical to that with wind nudging (not shown), so the details of the wind forcing structure are not considered critical.

To document the response of the model to the nudging indicated in Fig. 4, we averaged each model
integration over the month of June and computed the difference between the nudged forecasts and control (i.e., unnudged) forecasts. Furthermore, a statistical significance test for the difference in monthly means was performed at each grid point individually and independently, and only differences that are significant at the 1% level are displayed. We considered three distinct nudging experiments: L, A, and A + L.

The change in soil wetness in the three nudging experiments is shown in the left panels of Fig. 5. In the case of land-only nudging, the mean change in soil wetness (Fig. 5a) has spatial structure similar to the nudging of soil wetness (Fig. 4b). This similarity is a simple consequence of water conservation—water injected into the land by the nudging can change only by vertical transport because it is conserved and there is no horizontal transport in the land; however, the vertical transport in the corrected model does not accelerate sufficiently to compensate for the excess water. In contrast, if only atmospheric variables are nudged, then Fig. 5c reveals that there is virtually no soil wetness response, except for drying over a large area in central Africa. This drying over central Africa worsens the original dry bias in this location. We will see shortly that the dry bias arises from a reduction in precipitation as a result of a change in the regional circulation. Interestingly, the response to both land and atmospheric nudging is fairly well approximated by the sum of the responses to the individual nudgings.

FIG. 5. Difference between the June-mean corrected forecast and the June-mean control forecast for sw and st for three different experiments: (a),(b) land-only nudging; (c),(d) atmosphere-only nudging; and (e),(f) simultaneous land-atmosphere nudging.
The response of soil temperature to the three different nudgings is shown in the right panels of Fig. 5. Surprisingly, the response to land-only nudging is dominated by cooling, despite that nudging parameters seen in Fig. 4a act to warm about half the total land area. Note especially that the land correction in the Amazon acts to warm the land temperature, but the response is a net cooling. A clue to this puzzle is that the response structure seen in Fig. 5b is similar to the structure of the soil moisture forcing (Fig. 4b). This similarity suggests that evaporative cooling induced by soil moisture nudging dominates over the response to temperature nudging. In contrast, the response of soil temperature to atmosphere-only forcing, shown in Fig. 5d, shares many similarities with the atmospheric temperature forcing, shown in Fig. 4c, suggesting that the land temperature responds directly to the atmospheric cooling due to nudging. The main exception to this direct response is central Africa, which experiences land warming despite the atmospheric nudging tending to cool there. As we show next, this exception can be linked to a reduction in precipitation, which in turn leads to a reduction in evaporative cooling and hence anomalous heating.

The response of precipitation to the different nudgings is shown in Fig. 6. The similarity between Figs. 4b and 6a suggests that if only land variables are nudged, then the precipitation tends to increase over areas where nudging injects water into the soil. This result suggests the straightforward mechanism that water introduced into the land is transferred to the atmosphere where it precipitates regionally. In contrast, if only atmospheric variables are nudged, then the precipitation response (Fig. 6c) over
most land points tends to decrease, especially over central Africa, leading to drying. The change in soil moisture seen in Fig. 5c is consistent with the change in precipitation seen in Fig. 6c, in the sense that an excess or deficit of soil moisture is found in regions with excess or deficit of precipitation. The change in low-level atmospheric moisture is shown in the right column of Fig. 6. The similarity between the response to land forcing (Fig. 6b) and the soil moisture forcing (Fig. 4b) suggests that water injected into the land “diffuses” into the atmosphere and then advects downwind.

An interesting question is whether nudging improves the consistency between the simulated precipitation and the precipitation used to produce the GOLD dataset. The statistically significant differences between these two precipitation fields are shown in Fig. 7. The land-only correction (Fig. 7a) yields fewer differences than the control model, demonstrating that land-only correction brings the precipitation closer to the GOLD precipitation. However, most of the improvement is from dry to wet; regions with excess precipitation in the control model change only negligibly. The atmosphere-only correction (Fig. 7d) yields more differences than the control model, suggesting that it generally degrades the precipitation forecast. Overall, these results suggest that the precipitation may be “improved” more easily by correcting land than by correcting the atmospheric temperature and wind forcing.

To quantify the vertical structure of the response due to land nudging, we show in Fig. 8 the maximum height at which the land-only corrections produce statistically significant changes in the atmosphere. In general, the land correction has no significant effect on temperature and moisture above 1000 m except over equatorial landmasses, eastern Europe, eastern North America, Burma, and the Middle East. These latter regions coincide with regions of significant change in precipitation (Fig. 6a). The statistically significant changes in wind variables, which reflect a change in regional circulation, are concentrated primarily over equatorial landmasses. The fact that midlatitudes are characterized by insignificant changes in wind suggests that the land nudging does not significantly alter the general circulation in midlatitudes. It is interesting that although the land correction produces cooling and wetting in both midlatitudes and tropics, the regional circulation appears to be altered primarily in the tropics. Consistent with this, an atmospheric correction alters precipitation over land primarily in the tropics. These results suggest that the deep tropics probably experience a regional change in general circulation that is more complicated than the regional land–atmosphere interaction discussed earlier.

FIG. 7. Difference between the June-mean corrected forecast and the June-mean precipitation used to derive the GOLD dataset for four experiments: (a) L, (b) A + L, (c) no nudging, and (d) A.
Finally, the maximum height tends to be larger downwind from coastal boundaries and insignificant over the oceans, reflecting the moderating effect of maritime air on land–atmosphere feedback.

We performed several other statistical analyses of the deep tropics but were not able to formulate a satisfactory picture of why this region stands out relative to midlatitudes. We stress, however, that the mere fact that the deep tropics can be distinguished from midlatitudes based on its response to empirical corrections is a significant result.

Results for other variables generally support the picture described above. For instance, the response of downward shortwave and longwave radiation at the ground (not shown) has nearly the same structure as the precipitation response shown in Fig. 6. This similarity is not surprising, because the shortwave and longwave signals are dominated by cloud changes, which in turn are associated with precipitation changes. If only land variables are nudged, then the statistically significant changes in latent heat flux are predominantly positive and have an overall structure similar to the soil wetness nudging (Fig. 4b), consistent with the hypothesis that injecting water into land effectively injects water into the atmosphere. If only atmospheric variables are nudged, then the statistically significant changes in latent heat flux over land (not shown) are predominantly negative and are consistent with the decrease in precipitation shown in Fig. 6c. The response of sensible heat fluxes to nudging tends to be negatively correlated with the response of latent heat fluxes over land. This negative correlation is a simple consequence of energy conservation in each column, assuming the heat content of the soil does not change significantly over the month.

4. Summary and discussion

This paper proposed a new method for investigating coupled land–atmosphere interactions. The basic idea is to empirically correct a dynamical model multiple times, each time applying the correction to distinct components of the model individually, and then examine differences between the correction experiments. The empirical correction is a form of nudging, in which an estimate of the instantaneous tendency errors is subtracted from the forecast at each time step. The detailed structure of the nudging was found by estimating the initial tendency errors of the model at each day in the month of June during 1982–91 and then subtracting these errors at each time step [see DelSole et al. (2008) for further details]. Three distinct nudging experiments were examined: 1) nudging of land variables only (in particular, soil temperature and
soil wetness); 2) nudging of atmospheric variables only (in particular, temperature and winds); and 3) nudging of both atmosphere and land variables. The response to nudging was identified by the monthly-mean difference between the nudged run and the control run. Only differences that were significant at the 1% were considered.

The results present convincing evidence that much of the land–atmosphere coupling in midlatitudes can be understood from straightforward water balance considerations, whereas the coupling in the deep tropics involves a more complicated change in regional circulation. Specifically, when land variables are nudged, the response of soil wetness, soil temperature, precipitation, low-level atmospheric temperature, latent heat flux, and sensible heat flux all have structures similar to the soil wetness forcing. These similarities are consistent with a regional land–atmosphere interaction that transfers positive soil moisture anomalies to the atmosphere directly above, which in turn advect downstream and thereby moisten the atmosphere in the downwind regions to produce positive precipitation anomalies. Although both soil temperature and soil wetness were nudged at the same time in these experiments, the response was dominated by the soil wetness forcing, as indicated by the fact that virtually no area of soil heating leads to warming, but most areas with soil wetting leads to soil cooling. The evidence presented here for a regional land–atmosphere interaction is consistent with previous studies (e.g., Koster and Suarez 2003; Koster et al. 2004a).

In contrast, the response of atmospheric wind to land nudging, which measures the response of the general circulation, is not statistically significant except primarily over equatorial landmasses and the Indo-Asian monsoon region. This result suggests that land nudging alters the regional circulation primarily in the deep tropics, consistent with the hypothesis that the midlatitude response can be understood without invoking changes in the general circulation. Atmosphere-only nudging, which alters the general circulation, leads to significant precipitation anomalies primarily in the equatorial and Indo-Asian monsoon regions. These results suggest that the tropical circulation is more sensitive to nudging than midlatitudes.

Since the model is nudged toward an analysis and not to observations, differences between analyses and forecasts cannot be interpreted as true errors. This issue probably is not critical for atmospheric variables because 6-h analysis errors are much smaller than 1-month forecast errors. For land variables, the situation is more involved because our verification data for soil temperature and wetness are not direct observations but rather were derived by forcing a land model offline with observationally constrained estimates of fluxes. Nevertheless, because the land model in the GCM is identical to the land model that produced the GOLD dataset, large RMSEs in the land variables indicate large errors in the fluxes applied to the land model. Thus, the fact that nudging drives the simulated land variables closer to the offline estimates implies that the simulated fluxes are closer to the observationally constrained fluxes. This indirect approach to identifying errors in land variables seems unavoidable given the absence of global observations of soil wetness and temperature.

The above comments notwithstanding, it should be recognized that our conclusions regarding land–atmosphere coupling do not require that the verification be truth. A reasonable method for exploring dynamical systems is to insert an arbitrary perturbation in the system and then observe how the system responds. Examples of this approach include the Rossby adjustment problem, the response of the thermocline to wind stress anomalies, the teleconnection due to convective anomalies, and the general initial value problem. In each case, the perturbation itself need not be “physical.” Similarly, the nudging employed in this paper can be considered an exploratory forcing for eliciting land–atmosphere interactions.

Although the nudging need not be corrective to draw correct conclusions, the use of nudging based on tendency errors reduces the forecast errors and therefore gives insight into how the model will respond to potential model corrections. Such insight may be useful to model developers. For instance, our results show that the coupled model responds much more strongly to land moisture perturbations than to land temperature perturbations. This result suggests that a focus on improving the water balance may be more productive than improving the energy balance, at least to first order of correction. As another example, the experiments show that the model response to land nudging is dominated by a straightforward, regional interaction everywhere except in the deep tropics. This result suggests that a change in land surface model could improve the soil moisture field in midlatitudes by straightforward mechanisms, but that equatorial landmasses, such as central Africa, probably will require a different approach that accounts for the sensitivity of the regional circulation.

Although we estimated tendency errors using a regression technique, DelSole et al. (2008) note that the even simpler method of dividing the 24-h forecast error by 24 h gave similar tendency errors. Presumably, more accurate estimates of the tendency errors could be obtained from a data assimilation system because such a system would account for uncertainty in the state and the space–time structure of the errors. In fact, the nudging parameters can be included as part of the state vector, in which case the Kalman filter equations can be
applied to the augmented state vector to estimate the state and nudging parameters simultaneously. Although this approach has been demonstrated to work for simple models, applying it to large-scale models with parameters that vary in space (as in the present study) presents significant challenges. Yang and DelSole (2009) propose methods for overcoming these practical problems in the ensemble Kalman filter, including introducing memory in the parameter updates and applying covariance localization to both the state and parameters. In this more general approach, our nudging experiments would be replaced by assimilation experiments in which just land observations or just atmospheric observations are assimilated, and then differences between the assimilation experiments are examined.

Of course, our conclusions regarding the nature of the land–atmosphere interaction could be model dependent. However, as discussed in the introduction and illustrated in Figs. 1 and 2, forecast errors of the COLA model are similar to those of other models, and many of our results are consistent with the multimodel results of Koster and Suarez (2003) and Koster et al. (2004a). Moreover, our methodology for exploring land–atmosphere coupling is very general and can be applied to other models. In this sense, the results of this paper have implications that go beyond the particular model used to conduct this study.

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