Climate Dynamics (2006)
DOI 10.1007/s00382-006-0130-z

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The Big Brother Experiment and seasonal predictability in the NCEP regional spectral model

Received: 14 January 2005 / Accepted: 17 January 2006

Abstract The Big Brother Experiment methodology of Denis et al. (Clim Dyn 18:627-646, 2002) is applied to test the downscaling ability of a one-way nested regional climate model. This methodology consists of first obtaining a reference climate by performing a large domain, high resolution regional climate model simulation—the Big Brother. The small scales are then filtered out from the Big Brother's output to produce a data set whose effective resolution is comparable to those of the data sets typically used to drive regional climate models. This filtered data set is then used to drive the same nested regional climate model, integrated over a smaller domain, but at the same high resolution as the Big Brother - the Little Brother. Any differences can only be attributed either to errors associated with the nesting strategy and downscaling technique, or to inherent unpredictability of the system, but not to model errors. This methodology was applied to the National Center for Environmental Prediction Regional Spectral Model over a tropical domain for a 1-month simulation period. The Little Brother reproduced most fields of the Big Brother quite well, with the important exception of the small-scale component of the precipitation field, which was poorly reproduced. Sensitivity experiments indicated that the poor agreement of the precipitation at these scales in a tropical domain was due primarily to the behavior of convective processes, and is specific to the Big Brother Experiment on the tropical domain. Much better agreement for the small-scale precipitation component was obtained in an extratropical winter case, suggesting that one factor explaining the tropical result is the importance of convective processes in controlling precipitation, versus the greater importance of large-scale dynamics in the winter extratropics. In the tropical case, results from two ensembles of five 3-month seasonal simulations forced by GCM output suggest a considerably greater predictability for the small-scale stationary component of tropical precipitation than did the Big Brother Experiment.

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1 Introduction

Regional climate modeling has become an important tool for the prediction of climate variability and change. Many general circulation models (GCMs) still have resolutions too low to be able to resolve many features of interest. Thus limited-area, regional climate models (RCMs) have been used to produce climatic simulations of particular regions, with boundary conditions derived from observational data or a global GCM. The hypothesis behind the use of RCMs is that they can provide a correct representation of regional scale features which current GCMs do not resolve, at an affordable computational cost in comparison to that of running a GCM at sufficiently high resolution to resolve these same features (Giorgi 1990; Giorgi et al. 1994, 1999; McGregor 1997; Wang et al. 2004). RCMs are typically run for an integration time longer than two weeks, long enough to lose sensitivity to the initial atmospheric conditions. Nonetheless, the results of these models still depend on the lateral boundary conditions from a global model or a global observational analysis (Jacob and Podzun 1997; Castro and Pielke 2004). An example of such simulations includes the Project to Intercompare Regional Climate Simulations (Takle et al. 1999).

RCMs in principle solve the same partial differential equations as a global climate model, but on a subset of the actual global domain. At the artificial boundaries of the regional domain, the solution from the outer model is recast in the form of boundary conditions. This raises important questions since this procedure cannot, in general, be expected to yield correct results (Browning and Kreiss 1986; Oliger and Sundstrom 1978). In practice, it is found that the model results very much depend on the details of the nesting strategy. Regional climate modelers find sensitivity to nesting issues such as the domain size, specific placement of boundaries, and difference in resolution between inner and outer solutions critical to solving the above mentioned problem (Jones et al. 1995, 1997; McGregor 1997; Seth and Giorgi 1998).

The regional domain size and location are critical free parameters in the RCM. Regional modelers typically choose the regional domain to be large enough so that regional features of interest are not too close to the lateral boundaries. At the same time, the domain is usually chosen small enough so that the large-scale circulation in the regional model does not depart too much from that of the driving model data (Jones et al. 2002). These rules of thumb are reasonable, but it is not obvious that, even with the most judiciously chosen domain, the one-way nesting strategy on which regional climate modeling is largely built must yield good results in all cases.

We assess the dynamical downscaling skill of the version 97 regional spectral model (RSM) developed at the National Center for Environmental Prediction (NCEP) (Juang and Kanamitsu 1994; Juang et al. 1997) by implementing the so-called Big Brother Experiment (BBE) methodology, developed by Denis et al. (2002; see also Elía et al. 2002; Denis et al. 2003; Antic et al. 2004). Two sets of ensemble simulations are also considered when assessing this model's downscaling ability.

The BBE consists of several steps, as follows [see Figs. 1, 2 of Denis et al. (2002) for a graphic illustration]. The first step is the construction of a reference climate from a simulation using a high-resolution RCM simulation on a large domain (The Big Brother). The second step is the production of a low-resolution version of the reference climate, by applying some form of filter or smoothing to the output of the Big Brother simulation. The effective horizontal resolution of this downgraded reference climate data set should be comparable to that of a global climate GCM or other data set typically used to drive an RCM. This low-resolution reference climate is then used to drive the same RCM which was used to produce the Big Brother, integrated at the same resolution as the Big Brother, but over a smaller domain embedded in the large domain (the Little Brother). In principle, this is a 'perfect model' experiment: since the same model is used for both the Big Brother and Little Brother experiments, any difference in the solutions can only be attributed either to the nesting strategy, or to inherent unpredictability of the system, but not to model error or problems with the initialization or verification data. Nonetheless, it must be kept in mind that regional models are, in operational and research practice, not driven by upscaled versions of themselves, but by other models or data sets. Here, we find considerably lower predictability in a tropical BBE than in ensembles of tropical simulations forced by a GCM. In this case, it appears unwise to take the BBE as indicative of the skill of the model in its normal mode of operation. Further discussion follows.

Denis et al. (2002) performed their experiment over the North-American Eastern Seaboard for February 1993, using a grid point model. In that case, the BBE yielded good results. Small-scale low-level features that were absent from the initial and boundary conditions were almost fully recovered within the first day of the simulation. The Little Brother successfully reproduced the regional features of interest in the Big Brother, particularly in regions of strong surface forcing. Of particular interest here, precipitation was one of the fields that was well reproduced; even the small-scale component of the precipitation field (defined as scales small enough to be removed by the filter used to produce the low-resolution reference climate) was simulated with some skill.

Our study extends that of Denis et al. (2002) in two ways. We use a different model, the regional spectral model (RSM) developed at the National Center for Environmental Research (Juang and Kanamitsu 1994; Juang et al. 1997). Perhaps more importantly, we perform a tropical as well as an extratropical simulation. In the tropics, we expect convective processes to be more important than they are in the extratropics in winter, and it is reasonable to think that this difference might affect the predictability of regional features and thus the results of the BBE. Using a different model (particularly spectral vs. grid point) might also be expected to have some impact on the results. Doing both a tropical and an extratropical simulation, and comparing the results of these to each other as well as to those of Denis et al. (2002) allows us to determine which of these changes is more important. The predictability of the small-scale precipitation component is further examined with two ensembles of five ECHAM4.5 forced regional model simulations run for a 3-month period on the tropical domain.

In analyzing the results of our experiments, we focus closely on the small-scale component of the precipitation field. The precipitation field is inherently important for climate impacts, and is in many applications the forecast variable of greatest interest. The small-scale component is of particular interest because it is in producing that component that we can expect an RCM to add the value; the large-scale component is already available in whatever data are used to drive the regional model.

2 Model, experimental setup and analysis methods

The nesting method used by the RSM differs significantly from conventional methods used in regional modeling. Typical regional models, which are almost all grid point models, are forced by their outer coarse resolution data sets only in a lateral boundary zone. In this RSM, low-wavenumber information from the forcing data is used throughout the domain, with the regional model variables cast as perturbations on the forcing fields. The model is nonetheless fully nonlinear. Further details can be found in several studies (Juang and Kanamitsu 1994; Juang et al. 1997; Juang and Hong 2001; Sun et al. 2005).

Our tropical simulation domain is a part of the tropical Atlantic–South American region (Fig. 1). The RSM has been compared favorably to other models in a recent regional model intercomparison over this region (Roads et al. 2003). Downscaling of ECHAM4.5 AGCM seasonal predictions over the Nordeste and the North American continent with the RSM has also yielded encouraging results (Nobre et al. 2001). Both our Big Brother and Little Brother simulations are centered at 37.5°W and 5°S, with a spatial resolution of 60 km used for both domains. The Big Brother domain has 181×182 horizontal grid points, while the Little Brother has 91×92 horizontal grid points. Nineteen vertical levels were used in both simulations.

Our experiments were run for 1 month, chosen to be April 1994. This is during the region's rainy season (Sun et al. 2005), and the RSM yields relatively good results for this month when compared to the merged precipitation data set of Xie and Arkin (1996). The Big Brother simulation was driven directly by the ECHAM4.5 global model data set at T42 resolution, archived every 6 h. This ECHAM4.5 simulation is forced by the observed SSTs from 1948 to present. The Big Brother output was saved every 6 h as well, for the nesting of the Little Brother. The Little Brother was also run for 30 days, with the first day being discarded for the purpose of computing statistics to compare with the Big Brother.

To filter the output of the Big Brother before using it to drive the Little Big Brother, we simply remove all wave numbers higher than a cutoff value. The total wave number is used; that is, if k is the zonal wave number and l the meridional, we remove all wave numbers for which $k^2+l^2 > K_{\max}^2$, where $K_{\max}$ is the cutoff wave number. Wave numbers here are defined using sines and cosines on the Big Brother domain (as in the RSM itself), not using spherical harmonics on the globe. In order to mimic the resolution of the operational GCM (ECHAM4.5 at T42 resolution), we removed all wavenumbers larger than 11 (in our Big Brother domain) from the Big Brother output to produce the low-resolution reference climate data set used to drive the Little Brother. We filtered all of the prognostic variables: log of surface pressure, zonal and meridional wind, specific humidity, and temperature. For a set of sensitivity experiments, we also produced an additional set of reference climates with cutoff wave numbers of 5, 8, 14, 17, and 22, corresponding to minimum wavelengths of 2,160, 1,350, 770, 635, and 490 km.

To better understand the results of the tropical simulations, it proved instructive to perform a set of four additional simulations, identical to the Little Brother experiment except that each was initialized 6 h after the previous one, so that the last was initialized 24 h after the initial Little Brother.

Our midlatitude experiment domains are located over the North American continent. They are both centered at 70°W and 47°N, with the spatial resolution of 50 km used for both domains. The Big Brother domain has 151×142 grid points, while the Little Brother has 82×78. The location of our midlatitude domains is shown in Fig. 2. The time chosen for this experiment was February 2001.

2.1 Statistical methods

In this section we summarize the statistics we used to analyze our 1-month simulation. The statistics are similar to Denis et al. (2002).

Root mean square errors Root mean square error is defined by:

$$\mathrm{RMSE} = \sqrt{\sum_{i=1}^{n} \frac{(U_{\mathrm{BB}} - U_{\mathrm{LB}})^2}{n}}, \quad (1)$$

where U_{BB} and U_{LB} are, respectively, Big and Little Brother fields, and n is the total number of grid points

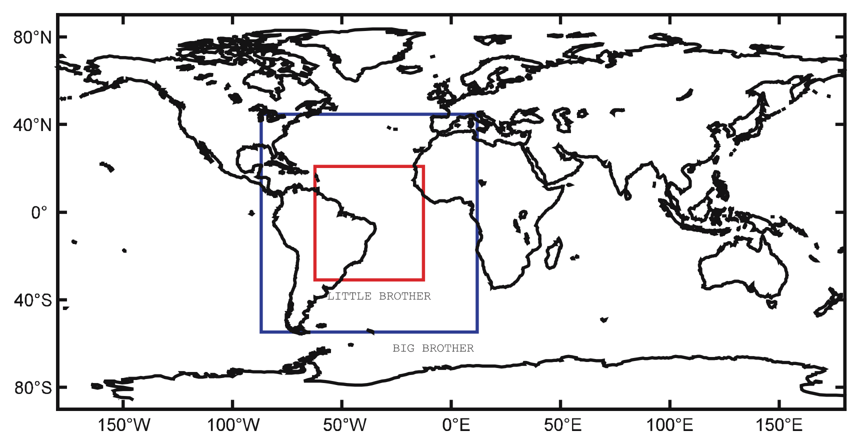

Fig. 1 Geographical boundaries of the tropical domains

(in space). Since we wanted a unitless reference, we have actually calculated the following ratio:

$$\text{Ratio} = \frac{\sqrt{\sum_{i=1}^{n}(U_{\text{BB}} - U_{\text{LB}})^2}}{\sqrt{\sum_{i=1}^{n} U_{\text{BB}}{}^2}}. \tag{2}$$

Spatial correlation coefficient Spatial correlation coefficient is defined as follows:

$$R = \text{CORRCOEF} = \frac{\sum_{i=1}^{n}(U_{\text{BB}} - \langle U\rangle_{\text{BB}})(U_{\text{LB}} - \langle U\rangle_{\text{LB}})}{\sqrt{\sum_{i=1}^{n}(U_{\text{BB}} - \langle U\rangle_{\text{BB}})^2 \sum_{i=1}^{n}(U_{\text{LB}} - \langle U\rangle_{\text{LB}})^2}}, \tag{3}$$

where $\langle U \rangle$ is a spatial averaging operator over n grid points:

$$\langle U\rangle = \frac{\sum_{i=1}^{n} U}{n}. \tag{4}$$

Stationary and transient variance ratios To complete the assessment of the Little Brother ability to reproduce stationary and transient small-scale behavior we define two variance ratios. Temporal decomposition for each variable U is given as a sum of its time mean (denoted by an overbar), and its time deviation (denoted by prime):

$$U(x,t) = \overline{U}(x) + U'(x,t). \tag{5}$$

Our filtering technique allows us to distinguish between large- and small-scale components of all fields. We define the ratio of domain-averaged stationary small-scale variances as:

$$\Gamma_{\text{ss}}^{\text{stat}} = \frac{\langle \overline{U}_{\text{ss}}^2\rangle^{\text{LB}}}{\langle \overline{U}_{\text{ss}}^2\rangle^{\text{BB}}}, \tag{6}$$

where "ss" denotes small-scale.

And, then we define the domain-averaged transient small-scales (denoted by subscript "ss") variances as:

$$\Gamma_{\text{ss}}^{\text{trans}} = \frac{\langle \overline{U_{\text{ss}}'^2}\rangle^{\text{LB}}}{\langle \overline{U_{\text{ss}}'^2}\rangle^{\text{BB}}}. \tag{7}$$

The variance ratios $\Gamma_{\text{ss}}^{\text{stat}}$ and $\Gamma_{\text{ss}}^{\text{trans}}$ provide us with the ability of the Little Brother to regenerate the spatial variance of the stationary and transient Big Brother small-scales.

3 Results

The fields discussed are surface temperature, precipitation, and specific humidity, and meridional and zonal winds at 850 hPa. We provide statistics for the total fields, as well as for the corresponding large/small-scale components, defined by removing wavenumbers larger/smaller than the cutoff wavenumber. This spectral filtering was performed by transforming the gridded output (itself generated from spectral fields in the case of most model variables, though precipitation is produced only in physical space) back to spectral space, removing the signal over the desired wave number ranges, and then transforming back.

3.1 Primary experiment

Surface temperature field Figure 3a, b shows the monthly mean surface temperature for both the Big and Little Brothers. The spatial correlation of the two is 0.99; the spatial correlation of the small-scale components only is 0.95. Table 1 displays the statistics of this field.

Precipitation field The time series of the domain average precipitation rates from the Big and Little Brothers are shown in Fig. 4. The two agree quite closely. The total precipitation over the whole month (excluding the spin-up period), is 118.5 mm for the Little Brother versus 113.4 mm for the Big Brother.

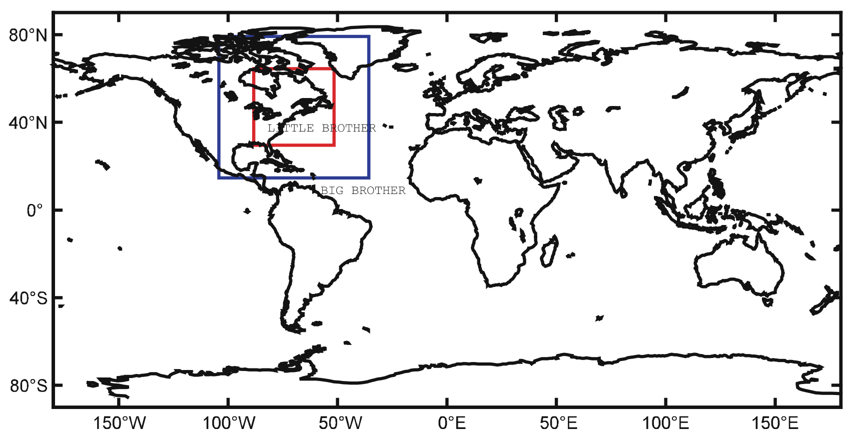

Fig. 2 Geographical boundaries of the extratropical domains

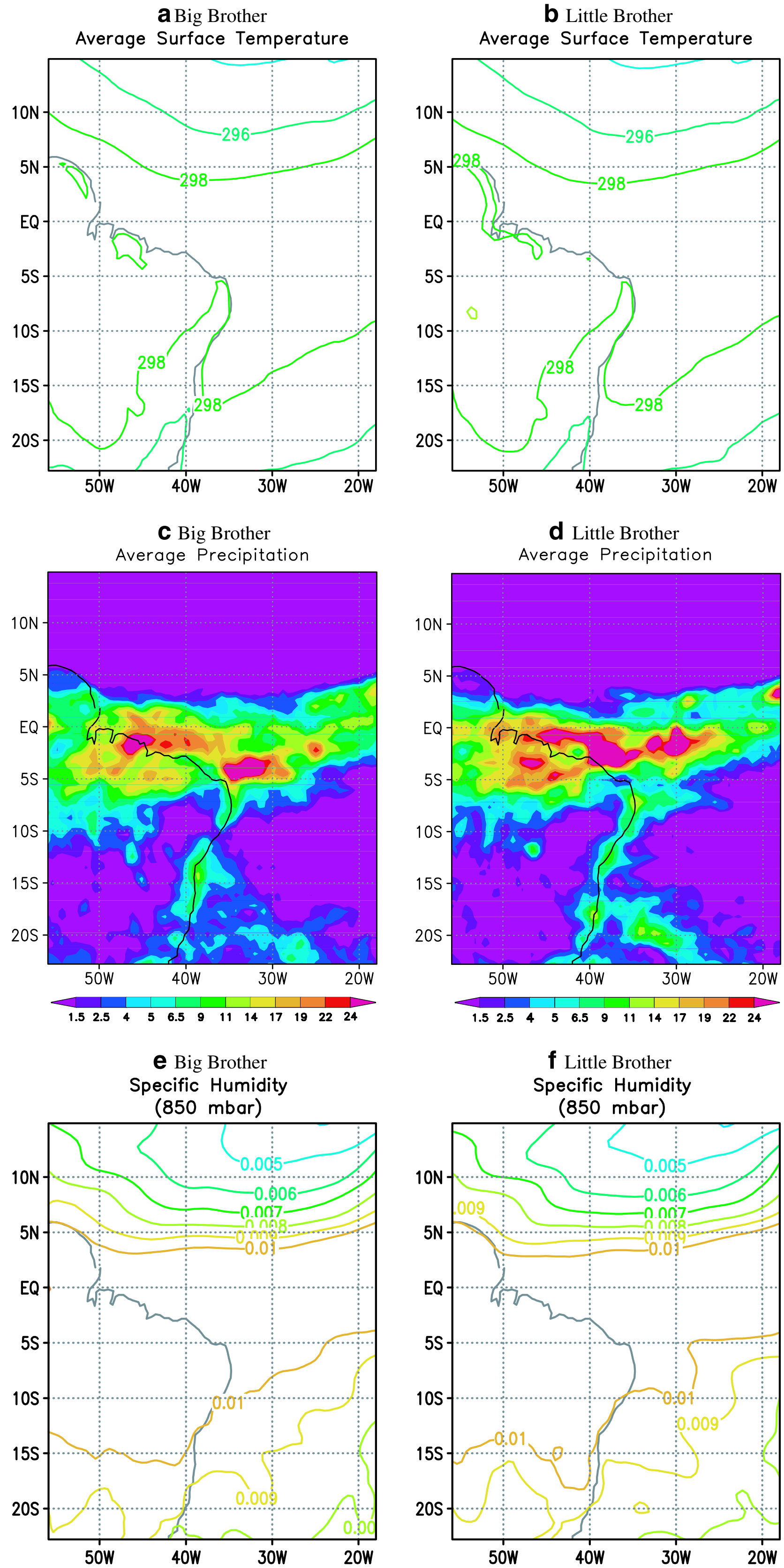

Fig. 3 Monthly mean surface temperature (**a**), precipitation rate (**c**), and specific humidity field (**e**), for the Big Brother; and corresponding monthly mean surface temperature (**b**), precipitation rate (**d**), and specific humidity field (**f**), for the Little Brother for our tropical domain

Table 1 Statistics of surface temperature, precipitation and specific humidity (850 hPa) for the tropical domain

Statistics	SFC temperature	Precipitation	SPEC humidity (850 hPa)
Total stationary correlation	0.99	0.81	0.99
Large-scale stationary correlation	0.99	0.85	0.99
Small-scale stationary correlation	0.95	0.22	0.99
Total transient correlation	0.83	0.31	0.77
Large-scale transient correlation	0.85	0.41	0.78
Small-scale transient correlation	0.66	0.11	0.60
Small-scale stationary variance ratio	1.03	1.74	1.01
Small-scale transient variance ratio	1.09	1.72	1.18
Small-scale RMSE ratio	0.29	1.46	0.18

Figure 3c and d shows the monthly mean precipitation rate for both the Big and Little Brothers. Table 1 shows the statistics of this field. The large-scale fields are similar, with a correlation of 0.81. However, the small-scale component shows poor agreement. The correlation of the stationary small-scale component is 0.22, of the transient small-scale component 0.11. The Little Brother also exhibits significantly more small-scale variance than the Big Brother, with $\Gamma_{ss}^{stat} = 1.73$ and $\Gamma_{ss}^{trans} = 1.71$. In accordance with the small small-scale correlation coefficient, the small-scale RMSE is large. We do not understand the large values obtained for the small-scale variances, but note that the same statistic is much improved in the extratropical winter simulation, as shown in Table 2 and that it decreases only to 1.53 when no filtering is applied to the Big Brother before using it to force the Little Brother (simulation not shown; but note that this simulation need not, as it does not, give identical results to the Big Brother, because it is forced with different boundary conditions due to the different domain sizes, as well as different large-scale fields since the Big Brother need not be identical to the GCM even at large scales), suggesting that that it is not primarily an artifact of the filtering.

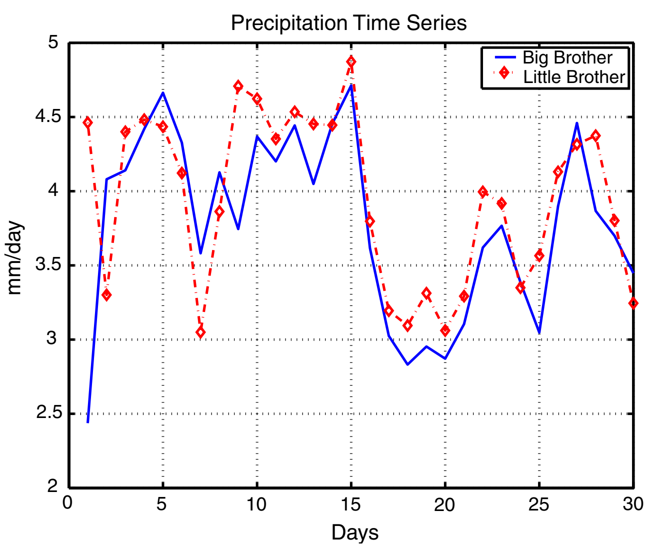

Fig. 4 Time series of the domain average precipitation rates for the tropical simulation

Figure 5 shows the time mean small-scale precipitation for our tropical domain for both the Big and Little Brothers. The distribution of small scales demonstrates the spatial difference in the small scales between the two domains: the agreement of the small scales is relatively good towards the middle of the domain; nevertheless, it decreases near the boundaries.

As in most models, the simulated precipitation in the RSM has two components: convective precipitation, meaning that produced directly by the convective parameterization; and resolved precipitation, meaning that which occurs due to condensation on the grid scale. It is of interest to determine what fraction of the small-scale precipitation is convective and what is resolved. Since the small-scale precipitation is comprised of a subset of wave numbers, it is not required to be positive and thus it is not particularly meaningful to state the ratio of the convective component (say) to the total small-scale precipitation. Instead, we compute the spatial correlation of the two components to the total, and the relative size of the spatial variances, for the stationary small-scale precipitation. The spatial correlation of the stationary resolved and stationary total small-scale precipitation is 0.81, while the spatial correlation of the stationary convective small-scale and stationary total small-scale precipitation was 0.74. The variance of the small-scale stationary convective precipitation is 35.5% of the magnitude of the stationary total small-scale precipitation, while the variance of the small-scale stationary resolved precipitation field to the total is 46.5% (the variances of the two components should not add up to the total variance, unless this covariance is zero).

These measures indicate that the convective and resolved components of the stationary small-scale precipitation are of comparable magnitude, and are also correlated with one another, so that the resolved precipitation (for example) could be controlled to some degree by the convective component. For example, when the convective scheme is activated, the resulting heating drives ascent, and the ascent moistens the atmosphere, making grid-scale condensation more likely. At a minimum, we can say that the convective precipitation is of considerable importance in this simulation, which will

Table 2 Statistics for the midlatitude domain case

Statistics	SFC temperature			Precipitation			SP humidity		
	Land	Sea	Total	Land	Sea	Total	Land	Sea	Total
Total stationary correlation	0.99	0.99	0.99	0.88	0.97	0.95	0.99	0.99	0.99
Large-scale stationary correlation	0.99	0.99	0.99	0.92	0.98	0.96	0.99	0.99	0.99
Small-scale stationary correlation	0.99	0.99	0.99	0.82	0.82	0.82	0.99	0.99	0.99
Small-scale stationary variance ratio	1.05	1.04	1.04	1.25	1.12	1.19	1.09	1.08	1.08
Small-scale transient variance ratio	0.95	0.97	0.95	1.24	1.24	1.21	1.05	1.07	1.05
Total transient correlation	0.89	0.92	0.90	0.72	0.75	0.73	0.91	0.88	0.91
Large-scale transient correlation	0.90	0.92	0.91	0.77	0.80	0.79	0.91	0.88	0.91
Small-scale transient correlation	0.81	0.88	0.85	0.44	0.40	0.39	0.85	0.88	0.87
Small-scale RMSE ratio	0.07	0.04	0.05	0.64	0.61	0.63	0.09	0.08	0.09

not be the case in our extratropical simulation shown below. The fraction of the total convective rain to total rain for the whole domain is 0.74 in the tropical case, while only 0.04 for the extratropical winter case.

Specific humidity field (850 hPa) Figure 3e and f shows the monthly mean specific humidity (850 hPa) for both the Big and Little Brothers. The two fields are quite similar, with spatial correlation of 0.99. The small-scale spatial correlation is 0.98. Table 1 below displays the statistics of this field. All show good agreement, though the Little Brother has slightly more transient small-scale variance than the Big Brother, $\Gamma_{\mathrm{ss}}^{\mathrm{trans}} = 1.18$.

Meridional and zonal wind fields Figure 6 shows the monthly mean meridional and zonal winds for both Big and Little Brother at 850 hPa. Table 3 displays the statistics of meridional and zonal wind fields at 850 hPa. The similarity between the two experiments is very high, with a total spatial correlation of 0.98 for zonal wind and 0.96 for meridional wind at 850 hPa. At other levels (not shown in the table), the total spatial correlation is similarly high: 0.99 for the zonal wind and the meridional wind at 1,000 hPa, 0.99 for the zonal wind and 0.89 for the meridional wind at 500 hPa and 0.99 for the zonal wind and 0.96 for the meridional wind at 200 hPa level. The small-scale spatial correlation is slightly smaller than the total spatial correlation, but still quite high: 0.96 for the zonal wind and 0.94 for the meridional wind at 850 hPa. The transient correlations are significantly lower than the stationary ones (for the large scales as well as the small scales) but even the lowest, the small-scale transient correlation, is 0.59, reasonable agreement. Generally, the zonal wind exhibits somewhat higher small-scale correlation for each level than does meridional wind. The Little Brother has slightly less small-scale stationary variance than does the Big Brother, and slightly greater transient variance.

3.2 Sea–land climate statistics

One hypothesis for the Little Brother's poor reproduction of the Big Brother's small-scale precipitation field might be that the lower boundary over a large fraction of our domain is ocean rather than land. We expect that stationary precipitation features over the land will be more tied to geographical features at the surface and hence be more reproducible in experiments such as ours. To test this, Table 4 shows the climate statistics for the surface temperature field, specific humidity field (850 hPa) and the precipitation field computed separately for land and the ocean. The total values computed earlier are shown, as well. The precipitation correlation

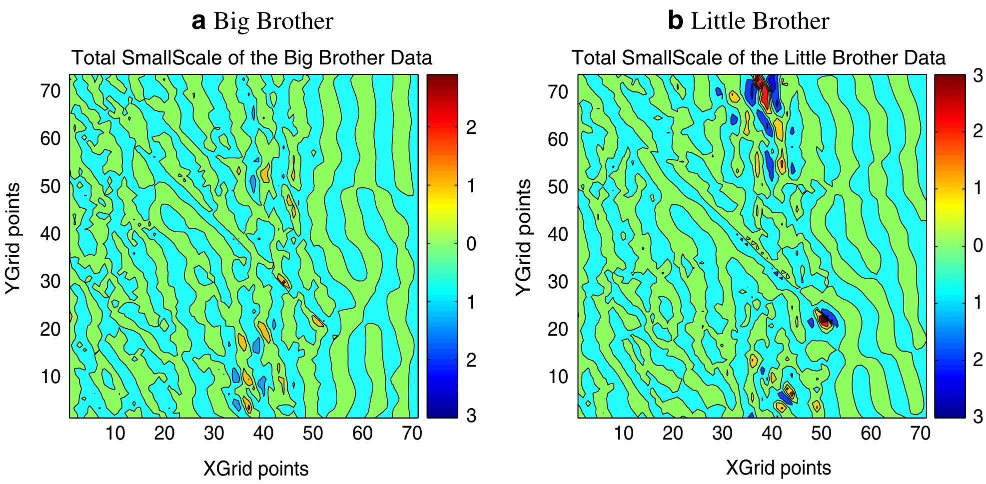

Fig. 5 Small-scale precipitation distribution of the **a** Big and **b** Little Brother on the tropical domain

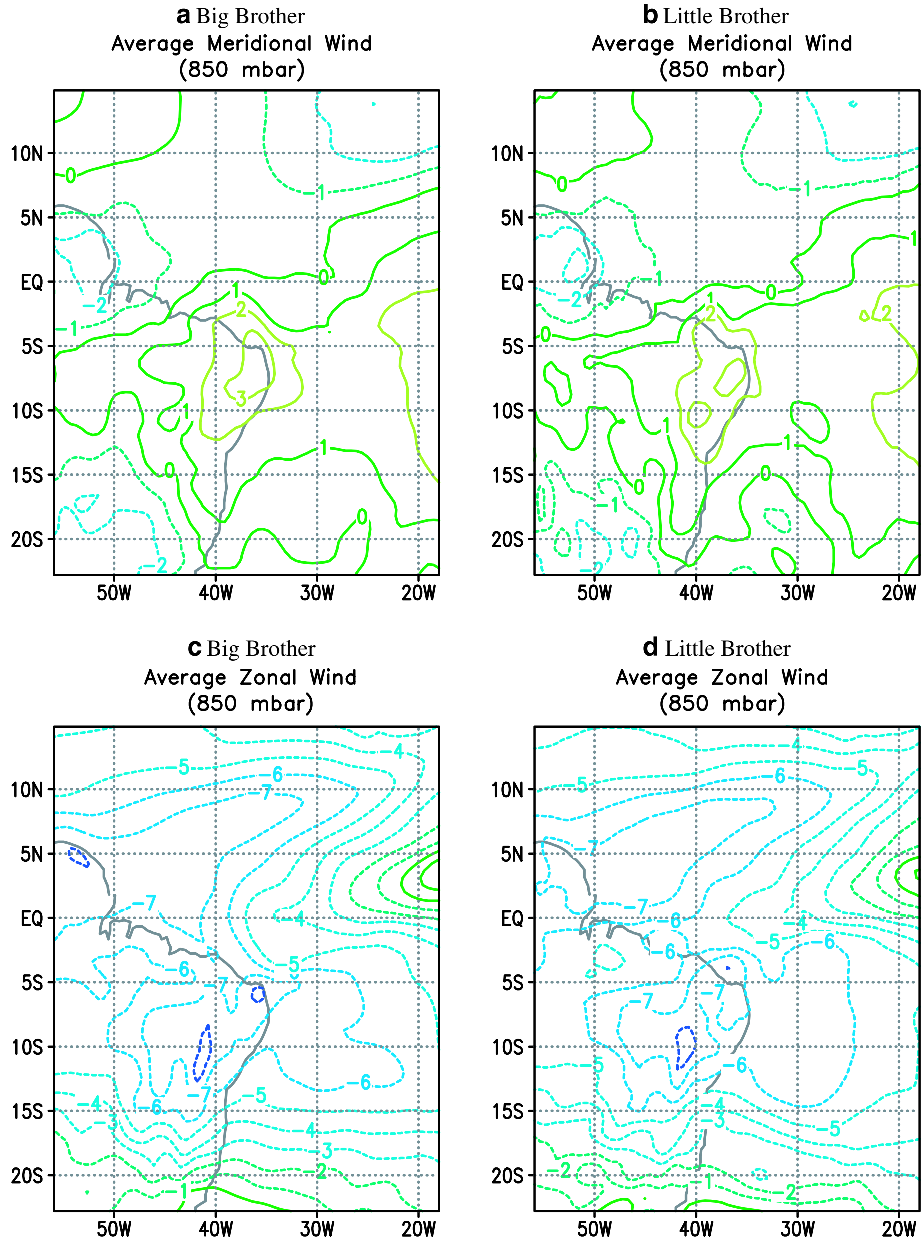

Fig. 6 Monthly mean meridional and zonal winds at 850 hPa. **a** and **c** The Big Brother; **b** and **d** the Little Brother

is slightly higher over the land than over the sea, while the values for the prognostic variables (specific humidity, temperature, zonal wind, meridional wind) are generally slightly higher over the ocean. The differences are small, however; the small-scale precipitation correlations are nearly as poor over land as over the ocean.

Table 3 Statistics of winds (850 hPa) for the tropical domain

Statistics	Meridional wind (850 hPa)	Zonal wind (850 hPa)
Total stationary correlation	0.96	0.98
Large-scale stationary correlation	0.96	0.98
Small-scale stationary correlation	0.94	0.96
Total transient correlation	0.76	0.88
Large-scale transient correlation	0.77	0.88
Small-scale transient correlation	0.59	0.73
Small-scale stationary variance ratio	0.85	0.87
Small-scale transient variance ratio	1.19	1.15
Small-scale RMSE ratio	0.35	0.09

3.3 Fixed wave-number cut-off comparison

To test the sensitivity of the results to the choice of the cutoff wave number, we performed an additional set of Little Brother experiments in which the Big Brother output was filtered with different cut-off wave-numbers before being used to drive the Little Brother. Figure 7 shows the small-scale precipitation correlation (with the Big Brother) and RMSE as a function of cutoff wave number. In this plot, the cut-off wavenumber was fixed at 11 for the purpose of defining what is small-scale for the computation of statistics, though it was varied in

Table 4 Land–sea statistics for the tropical domain

Statistics	SFC temperature			Precipitation			SP humidity		
	Land	Sea	Total	Land	Sea	Total	Land	Sea	Total
Total stationary correlation	0.99	0.99	0.99	0.88	0.78	0.81	0.98	0.99	0.99
Large-scale stationary correlation	0.99	0.99	0.99	0.93	0.82	0.85	0.98	0.99	0.99
Small-scale stationary correlation	0.95	0.96	0.95	0.26	0.21	0.22	0.98	0.98	0.98
Small-scale stationary variance ratio	1.02	1.04	1.03	1.49	1.86	1.74	1.01	0.98	0.98
Small-scale transient variance ratio	1.05	1.13	1.09	1.75	1.89	1.72	1.21	1.17	1.18
Total transient correlation	0.86	0.73	0.83	0.37	0.28	0.31	0.69	0.78	0.77
Large-scale transient correlation	0.88	0.78	0.85	0.46	0.37	0.41	0.70	0.79	0.78
Small-scale transient correlation	0.66	0.65	0.66	0.14	0.09	0.11	0.51	0.61	0.60
Small-scale RMSE ratio	0.30	0.15	0.29	1.36	1.51	1.46	0.19	0.17	0.18

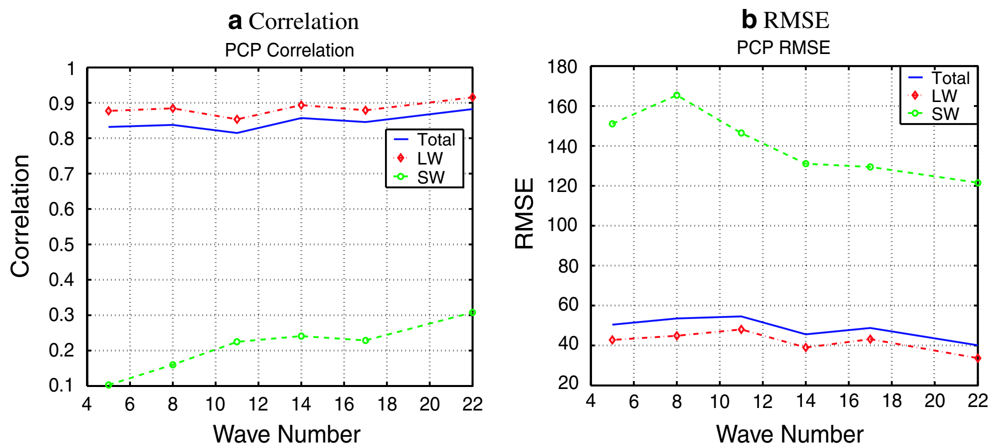

Fig. 7 Small-scale precipitation correlation (**a**) and RMSE (**b**) dependence on the wave-number, keeping the definition of the 'small-scale' fixed

producing the initial and boundary data sets. We have also computed the same curve varying the cutoff wave-number for the statistics calculation in the same way as for the initial and boundary data sets (not shown), and the results are not significantly different. For the small-scale component in particular, the correlation increases and the RMSE decreases (after wavenumber 10) somewhat as a function of cutoff wavenumber, as should be expected since more information from the Big Brother is being included in the driving data. The improvement is not great, however, with small-scale precipitation correlation remaining low and RMSE high for all of the experiments. Furthermore, at cutoff wavenumber equal to the maximum total wavenumber of the domain, i.e. no filtering, the small-scale features produced by the Big Brother are still not well reproduced by the Little Brother. In other words, even including all of the information from the Big Brother to force the Little Brother, we are still unable to reproduce the greater portion of the Big Brother's small-scale features.

3.4 Little Brother ensemble simulations

We performed a small ensemble of four additional Little Brother simulations (for a total of five including the original one), each using the same data set (from the filtered Big Brother) for initial and boundary conditions, the only difference being that each was started in a 6-h increment later than the previous one. We computed the same statistics as in the previous section, but now comparing the different Little Brother experiments to each other, rather than to the Big Brother. The results are generally similar to those from the previous comparisons of the first Little Brother to the Big Brother. In particular, the small-scale precipitation correlations still remain low. The results are summarized in Table 5. The initial implication is that for this domain, small-scale tropical precipitation features seems to have a small signal to noise ratio. However, we will see below that this improves dramatically when the regional model is forced by GCM output, rather than by the Big Brother.

3.5 Sensitivity experiments using various filtering options

The experiments described in this section were carried out in an attempt to isolate the reason for the low correlations and large variance ratios of the small-scale of the precipitation fields found in the tropical BBE. The statistics of all experiments described here are shown in Table 6.

Table 5 Precipitation field: (comparison of the Little Brother (00 h) to other ensemble members)

Statistics	Little Brother (6 h)	Little Brother (12 h)	Little Brother (18 h)	Little Brother (24 h)
Total stationary correlation	0.90	0.87	0.78	0.88
Large-scale stationary correlation	0.94	0.91	0.82	0.92
Small-scale stationary correlation	0.36	0.32	0.23	0.23
Small-scale stationary variance ratio	0.91	0.80	1.05	0.94
Small-scale transient variance ratio	1.07	1.09	1.29	0.99
Total transient correlation	0.37	0.32	0.24	0.31
Large-scale transient correlation	0.47	0.41	0.31	0.43
Small-scale transient correlation	0.13	0.10	0.06	0.06
Small-scale RMSE ratio	1.11	1.11	1.26	1.22

3.5.1 Experimental setup

Big Brother forcing field at 300 km spatial resolution The forcing Big Brother simulation was rerun at 300 km spatial resolution, and then used to drive the Little Brother. The low-resolution Big Brother had 54×55 grid points, occupying a somewhat larger spatial area than the original simulation. The time frame and time updating frequency remained the same.

Big Brother Experiment with unfiltered log(p_s) This experiment was identical to the original BBE, except that the log (p_s) field from the Big Brother was not filtered before it was used to drive the Little Brother. This experiment was motivated by a hypothesis that in a domain with some topographic relief, filtering of the topography might cause some problems.

Big Brother experiment with time and space filter In this experiment, the Big Brother output was filtered in time as well as space before it was used to drive the Little Brother. A three-point running mean was used for the time filtering; with data every 6 h, this means that each update of the forcing data represents an 18-h mean centered on the update time. This experiment was motivated by the recognition that the updating period of 6 h could be of the same order as organized convection internal variability time scale. Thus in a domain where there is very much convection, there could be some sensitivity.

None of these sensitivity experiments showed any significant improvement in the small-scale precipitation statistics, with one exception. The simulation in which the Big Brother was run at low horizontal resolution showed a significant decrease in the small-scale stationary variance ratio, to 1.34 from 1.74 in the original BBE. The small-scale correlations were not improved in this experiment. Nonetheless, this is consistent with the idea that something about the BBE setup itself, in which a regional model is forced by itself run at the same resolution (though filtered to lower resolution) is responsible for the large variance small-scale variance ratio found in the original BBE. The results of the following section confirm this.

3.6 ECHAM4.5 forced seasonal regional model ensemble simulations

Since the results of Sect. 3.4 suggested inherent predictability of the small-scale component of tropical precipitation as the reason for the poor skill in that component in the BBE, we carried out two additional sets of ensemble experiments to investigate that issue further. These experiments were forced by GCM output, since that is the way the model is actually used in operational practice. In the first set of experiments, an ensemble of five regional model simulations was forced by a single ECHAM4.5 simulation. This is appropriate for assessing loss of predictability due to the dynamics of the regional model alone. In the second set of experiments, five regional model simulations were forced by different ECHAM 4.5 simulations from an ensemble run with that GCM. This is a more appropriate way to assess the likely predictability in a real forecasting situation, where no GCM simulation can be taken as truth.

Table 6 Statistics of precipitation for various Big Brother experiments performed

Statistics	PCP orginal exp	PCP 300 km	PCP no filter log(p_s)	PCP time filter)
Total stationary correlation	0.81	0.78	0.89	0.84
Large-scale stationary correlation	0.85	0.81	0.93	0.88
Small-scale stationary correlation	0.22	0.17	0.29	0.28
Total transient correlation	0.31	0.07	0.39	0.23
Large-scale transient correlation	0.41	0.08	0.50	0.30
Small-scale transient correlation	0.11	0.04	0.09	0.06
Small-scale stationary variance ratio	1.74	1.34	1.73	1.88
Small-scale transient variance ratio	1.72	1.58	2.06	1.90

The simulations were performed using initial and boundary conditions from March to May (MAM) of 1994. This includes the period of the BBE, but is longer. This allows us investigate, among other issues, the dependence of the apparent skill on the length of the averaging period.

For the regional model ensemble simulations forced by the same ECHAM4.5 simulation, statistics are shown in Table 7. The 3-month small-scale spatial correlation is at 0.77, while bi-monthly was 0.70, and single month correlation was 0.61. There is some dependence on the averaging period, but even for a single month this result is greatly improved over the same statistic computed from the BBE. Variance ratios were between 0.9 and 1.1 for all averaging periods. Statistics for the simulations forced by five different ECHAM4.5 ensemble members are shown in Table 8. The 1-month correlations are low in absolute terms, but still significantly higher than those obtained for the Little Brother experiments.

3.7 Extratropical experiment

Our results for the small-scale precipitation component in the 1-month tropical Little Brother experiments described above are significantly poorer than those of Denis et al. (2002). This component was found to be more predictable in the experiments of Denis et al. (2002). Two factors might possibly explain this difference: the fact that our domain was tropical while theirs was extratropical, or the fact that our model is different than theirs. To determine which factor is more important, we performed an extratropical winter experiment using the RSM. The domains were placed over North American continent and centered at 47°N, and 70°W; Big Brother with 151×142 grid points, and Little Brother 82×78 grid points, at 50 km horizontal resolution. Figure 2 shows the location of the midlatitude domains. Statistical analysis of the results was performed similarly to the tropical experiment. We excluded the spin-up period (24 h), and the lateral blending zone (10 grid points), and computed statistics separately for land and ocean as well as for the whole domain. Our cutoff wavenumber was again chosen to correspond to a T42 resolution, which means that we keep the first seven waves in this case. This experiment was completed for the February of 2001. An additional midlatitude experiment was also performed for the same size domains but centered at 60°N, and 85°W, for the July of 1993, yielding similar results. This extratropical part of the experiment basically verifies the Denis et al. (2002) result. It would be interesting to see what their model would have yielded in the tropics.

Figure 8 and Table 2 show the surface temperature field, 850 hPa specific humidity field, and precipitation field from the extratropical experiment. These results demonstrate that placing the domain in the extratropics dramatically improves the simulation of the small-scale precipitation component. The stationary small-scale precipitation correlation increased from about 0.22 in tropical case to about 0.82. This is actually a larger value than that obtained by Denis et al. (2002) for the small-scale precipitation field in their simulations. The stationary correlations for the other fields are all greater than 0.90. As in the tropical case, the Little Brother reproduced the domain-averaged precipitation of the

Table 7 Correlations and variance ratios of the small-scale stationary component of the precipitation field for the Little Brother ECHAM4.5 Forced RSM Ensemble Simulations

ENS	1-month averages				2-month averages				3-month averages			
	S.S.C.	S.S.V.	S.T.C.	S.T.V.	S.S.C.	S.S.V.	S.T.C.	S.T.V.	S.S.C.	S.S.V.	S.T.C.	S.T.V.
Ens Avg	0.61	0.92	0.23	1.05	0.70	0.95	0.23	1.07	0.77	0.94	0.23	1.03

S.S.C Small-scale stationary corr; *S.S.V* Small-scale stationary variance ratio; *S.T.C* Small-scale transient corr; *S.T.V* Small-scale transient variance ratio
One-month values represent the average statistics over all independent pairs of ensemble members separately for March, April and May. Two-month values represent the average statistics over all independent pairs of ensemble members separately for March–April and April–May. A total of five simulations was performed, each initiated 6 h after the previous one.

Table 8 Correlations and variance ratios of the small-scale stationary component of the precipitation field for the Little Brother ECHAM4.5 Forced RSM Ensemble Simulations

ENS	1-month averages		2-month averages		3-month averages			
	SS. St. Corr.	SS. St.Var.	SS. St. Corr.	SS. St.Var.	SS. St. Corr.	SS. St.Var.	SS.Tr. Corr.	SS. Tr. Var.
Ens Avg	0.43	0.89	0.54	0.94	0.64	0.90	0.02	1.13

One-month values represent the average statistics over all independent pairs of ensemble members separately for March, April and May. Two-month values represent the average statistics over all independent pairs of ensemble members separately for March–April and April–May. Transient statistics are shown only for the full 1-month period

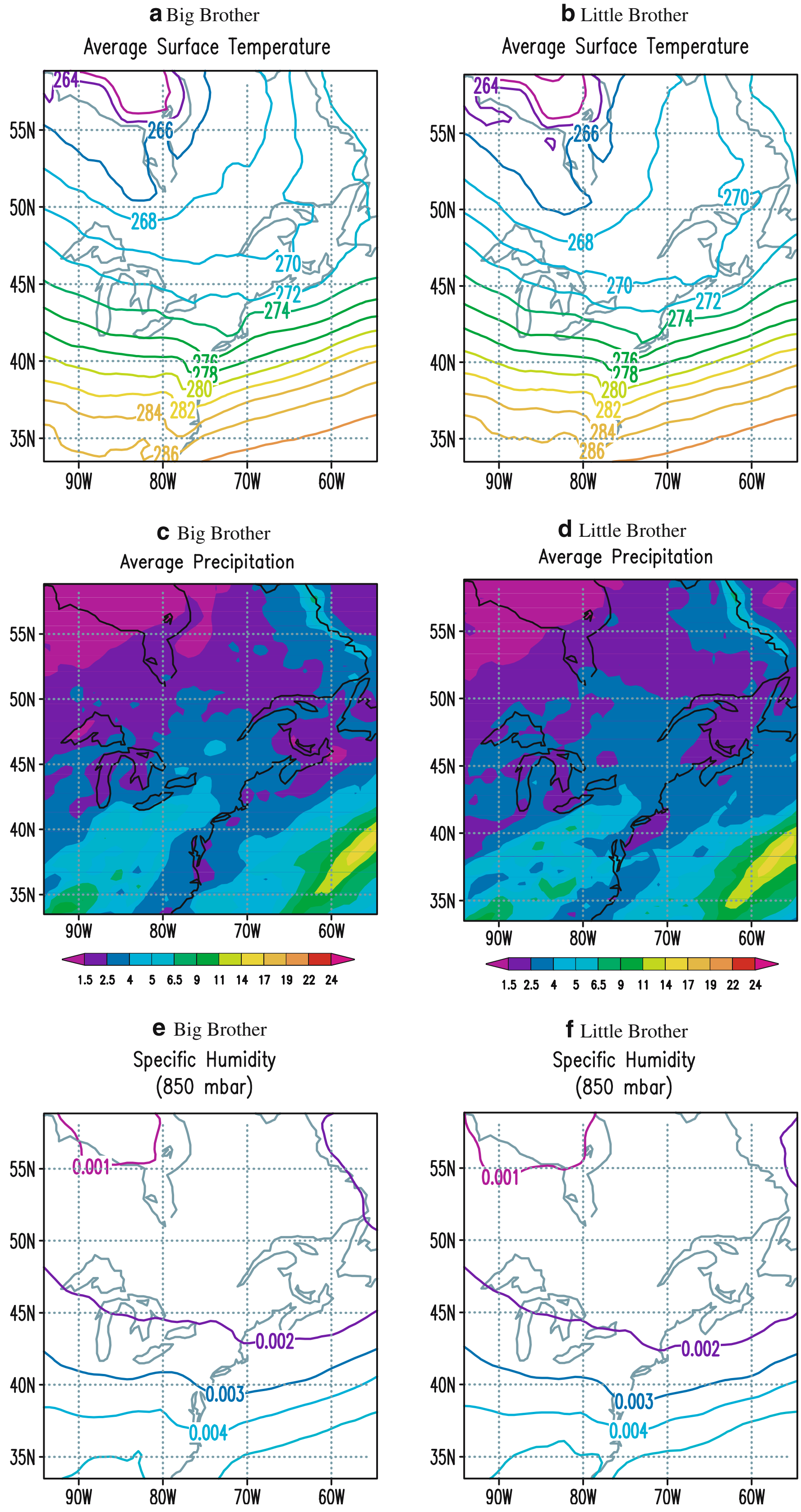

Fig. 8 Monthly mean surface temperature (**a**), precipitation rate (**c**), and specific humidity field (**e**), for the Big Brother; and corresponding monthly mean surface temperature (**b**), precipitation rate (**d**), and specific humidity field (**f**), for the Little Brother for our midlatitude domain

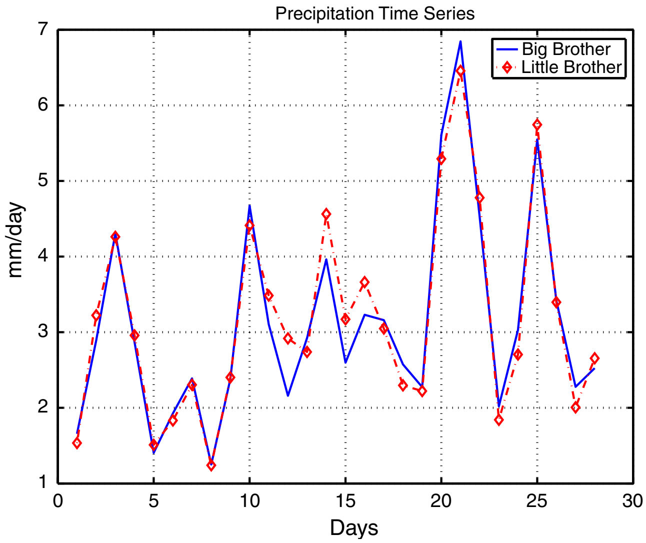

Fig. 9 Time series of domain average precipitation rate for the extratropical winter simulation

Big Brother very well: 88.7 versus 87.5 mm for the Big Brother. This is shown in Fig. 9.

It is reasonable to hypothesize that the fact that extratropical winter precipitation is largely controlled by large-scale dynamics while tropical precipitation is largely controlled by deep convection explains the difference between our tropical and extratropical simulations. This is confirmed by examining the relative importance of convective vs. resolved precipitation in the extratropical case. The spatial correlation of the stationary convective small-scale and stationary total small-scale precipitation is 0.69, while the spatial correlation of the stationary resolved small-scale and stationary total small-scale precipitation was 0.99. The spatial variance of the stationary convective small-scale precipitation is 1.3% of that of the total, while the variance of the stationary resolved small-scale precipitation field is 85.5% of that of the total (again, remember that the variances of the two components should not add up to the variance of the total). Thus in contrast to the tropical simulation, convective precipitation plays almost no role at small scales in the extratropical winter simulation. Furthermore, the average fraction of the convective rain to total rain for the whole domain is 0.04, clearly demonstrating the importance of the synoptic processes in the midlatitudes during the wintertime.

We also performed a summer extratropical simulation (July 1993), over the same domain as the extratropical winter case described above. We do not describe this in detail, but present a few statistics. The spatial correlation of the stationary convective small-scale and stationary total small-scale precipitation was 0.64, while the spatial correlation of the stationary resolved small-scale and stationary total small-scale precipitation was 0.88. These results are much closer to those of the extratropical winter simulation than to those of the tropical BBE. Apparently, that is because even in summer, large-scale dynamics plays an important role in controlling extratropical precipitation. The ratio of the convective to total precipitation over the whole domain for the extratropical summer case was 0.078.

4 Discussion and conclusions

The main objective of this study was to test the hypothesis under which the RCMs are used. Is the one-way nesting strategy, in which part of the solution is recast as boundary conditions (and in the case of the RCM, forcing on the large-scale fields in the interior) valid? We applied the Big Brother Experiment methodology developed by Denis et al. (2002) to a different model, the NCEP RSM, and to a different domain, this time in the tropics. Our main results are the following:

- In most fields, good agreement between Big and Little Brothers was obtained, for both small and large scales, after a brief initial spin-up period.
- Precipitation was the exception. For our 1-month tropical domain experiment, the small-scale features of the precipitation field in the Big Brother were not well reproduced by the Little Brother. The spatial and temporal variations of the large-scale component of the precipitation were well reproduced.
- An ensemble of identically forced Little Brother simulations, differing only in their initialization time (differing by 6–24 h) showed small-scale precipitation correlations nearly as low as that between the Big and Little Brothers. Taken alone, these results suggested the possibility that inherent low predictability of the small-scale component of tropical precipitation, rather than the nesting strategy per se, might be the key limitation in the results of the BBE. To investigate this issue further, we performed two ensembles of regional model simulations for a 3-month period, forced by the ECHAM4.5 over the tropical Little Brother domain. Two different types of simulations were performed: one using a single ECHAM4.5 simulation to force an ensemble of five RSM simulations; and secondly using five different ECHAM4.5 ensemble members, each forcing one RSM simulation.
- However, two ensembles of 3-month, GCM-forced simulations for our tropical 'Little Brother' domain contradict this. An ensemble of regional model simulations forced by a single GCM simulation showed dramatically improved statistics for the small-scale precipitation component. Even regional model simulations forced by different GCM ensemble members showed considerably better statistics for this component than did the simulations forced by the Big Brother.
- Very good reproduction of the small-scale precipitation was obtained for an extratropical winter simulation.

We are left with a mixed message. On one hand, the tropical BBE has a very low signal to noise ratio for the small-scale component of the tropical precipitation. While our simulations are completed as downscaling of boundary forcing rather than true prediction experiments, the situation will presumably not improve in forecast mode, which (from the atmosphere's point of view) differs only in that there are errors in the boundary forcings; results obtained from downscaling known boundary forcings give an upper bound on predictability. Thus, our results suggest that the regional model is incapable of predicting the small-scale component of tropical precipitation, arguably the most important aspect of the simulation. That component appears to be inherently unpredictable in the BBE framework. However, our other experiments show that this lack of predictability occurs only in the tropical BBE, and not in GCM-forced regional model simulations in a tropical domain, nor in an extratropical BBE. We must conclude that in this instance the BBE is not an adequate guide to the capabilities of the regional model in the context in which it is most commonly used. At present, we do not have a mechanistic understanding of the reason for the divergence between the BBE and the GCM-forced simulations. Several indicators point to deep convection as an important factor, but we are unable to make a more precise or detailed statement than that. To gain more insight into this issue, it would be desirable to perform similar experiments with different RCMs, different geographical locations (in both the tropics and extratropics), and for different durations, different seasons and different spatial resolutions.

Acknowledgments We thank Mark Cane for discussions. This research was supported in part by National Science Foundation grant DMS-01-39830, and in part by the International Research Institute for Climate and Society, Columbia University from the National Oceanic and Atmospheric Administration cooperative agreement NA07GP0213. The views expressed herein are those of the author(s) and do not necessarily reflect the views of NOAA or any of its sub-agencies. The first author also acknowledges the support from the US National Science Foundation, through a Fellowship in the IGERT Joint Program in Applied Mathematics and Earth and Environmental Science at Columbia University.

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