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A review on regional dynamical downscaling in intraseasonal to seasonal simulation/prediction and major factors that affect downscaling ability

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Regional climate models (RCMs) have been developed and extensively applied for dynamically downscaling coarse resolution information from different sources, such as general circulation models (GCMs) and reanalyses, for different purposes including past climate simulations and future climate projection. Thus far, the nature, the methods, and a number of crucial issues concerning the use of dynamic downscaling are still not well understood. The most important issue is whether, and if so, under what conditions dynamic downscaling is really capable of adding more information at different scales compared to the GCM or reanalysis that imposes lateral boundary conditions (LBCs) to the RCMs. There are controversies regarding the downscaling ability. In this review paper we present several factors that have consistently demonstrated strong impact on dynamic downscaling ability in intraseasonal and seasonal simulations/predictions and future projection. Those factors include setting of the RCM experiment (e.g. imposed LBC quality, domain size and position, LBC coupling, and horizontal resolution); as well as physical processes, mainly convective schemes and vegetation and soil processes that include initializations, vegetation specifications, and planetary boundary layer and surface coupling. These studies indicate that RCMs have downscaling ability in some aspects but only under certain conditions. Any significant weaknesses in one of these aspects would cause an RCM to lose its dynamic downscaling ability. This paper also briefly presents challenges faced in current RCM dynamic downscaling and future prospective, which cover the application of coupled ocean–atmosphere RCMs, ensemble applications, and future projections.

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1 . Introduction

Although regional climate models (RCMs), which evolved from mesoscale atmospheric models, have been applied for dynamic downscaling since the late 1980s (e.g., Dickinson et al., 1989; Giorgi and Bates, 1989; Kida et al., 1991; Juang and Kanamitsu, 1994; Bosilovich and Sun, 1999; Leung and Ghan, 1999; Laprise et al., 2000; Liang et al., 2001; Xue et al., 2001; Castro et al., 2005), the extensive applications of this approach have taken place only during the last decade. Today, this approach is widely applied not only for downscaling past climate, but also for future climate projection and many other applications such as producing high resolution data for hydrological assessments (e.g., Shukla and Lettenmaier, 2013). In these types of studies, the lateral atmospheric boundary conditions (LBC), the initial surface conditions, and some surface boundary conditions, such as sea surface temperature (SST) and sea ice, for the RCM are provided by the analysis of observational data (e.g., Laprise et al., 2000), atmospheric general circulation models (AGCMs, e.g.; Dickinson et al., 1989), coupled atmosphere–ocean GCMs (AOGCM, e.g.; Liang et al., 2008), or reanalysis data sets (e.g., Xue et al., 2001), such as the NCEP–NCAR Global Reanalysis (Kalnay et al., 1996). For simplicity, we use the abbreviation “GCM” for “AGCM” in this paper. As RCMs become more extensively applied for downscaling studies, it is important to understand whether and, if so, under what conditions the dynamic downscaling is really capable of improving simulation/prediction and/or adding more climate information at different scales compared to the GCM or reanalyses that impose LBCs to the RCM (e.g., Denis et al., 2002; Castro et al., 2005; Xue et al., 2007). The assumption behind such applications is that the RCM should at least reproduce the large scale characteristics of the GCM results or reanalyses which drive the RCMs and add more information at different, especially finer, scales. However, there are wide gaps between our understanding of this issue and the demands to apply dynamic downscaling for many applications. Some studies have suggested that some RCMs' applications seem beyond their real downscaling ability (e.g., Pielke and Wilby, 2012; Pielke, 2013; Mearns et al., 2013). We hope that this review will provide useful information for further studies of this problem.

Most RCMs originated from limited area mesocale models (e.g., Dickinson et al., 1989; Juang and Kanamitsu, 1994; Xue et al., 2001), and in most cases they actually did not conduct any “regional climate predictions,” which is the definition of RCM in the Glossary of Meteorology of the American Meteorological Society. This is in contrast to the GCM (i.e., general circulation model), which is labeled as a “global climate model” only when used for climate prediction. The widely used “climate downscaling” concept mainly refers to “climate” statistics based on averages of the climate system over periods of a month or more. RCMs have been applied for various temporal scales. This review paper focuses on intraseasonal to seasonal scales because most RCM studies focus on these scales, with some discussions on the interannual variability of seasonal features. At the end of this paper, we discuss issues regarding long term downscaling for future projection since RCMs have been widely used for such studies recently.

One distinct advantage of RCM application is its higher horizontal resolution, which enables the RCM to handle more realistically certain critically important climate processes, such as clouds and land surface processes/features (e.g., topography), especially when RCM provides cloud-permitting resolutions to avoid the cumulus parameterization issues. Studies have shown that with more detailed information over mountain ranges and coastal regions, RCMs are capable of reproducing the formation of mesoscale phenomena (e.g., Feser et al., 2011; Di Luca et al., 2012; Stefanon et al., 2013) as well as high resolution climate features. For instance, it is found that the core of the summer South American low level jet located east of the Andes is well simulated only in the RCM; there is no noticeable jet structure in the GCM outputs which imposed LBCs to that RCM (De Sales and Xue, 2006). Ikeda et al. (2010) also showed that in Colorado, 4-km resolution was needed to resolve elevations for correctly simulating snow-pack in high mountains.

However, conceptually, such advantage could disappear after development of GCMs with higher resolutions that are becoming feasible due to ever increasing computing power. Whether and how long the RCMs will be used will depend on how successful the dynamic downscaling is. The high resolution GCMs in principle appear to be a useful tool for exploring this issue. Unfortunately, thus far, there have not been many such studies carried out with full scientific rigor. In a model intercomparison project, the West African Monsoon Modeling and Evaluation (WAMME, Xue et al., 2010a; Druyan et al., 2010), both GCMs and RCMs were employed for seasonal simulations. The GCM results in Fig. 1a and b are from the Japan Meteorological Administration Meteorological Research Institute (JMA MRI, Mizuta et al., 2006) GCM with about 20-km resolution and the U.K. Meto Office HadAM3 GCM with 2.5° × 3.75° (Pope et al., 2000), respectively. The RCM downscaling results using the HadAm3 as LBC, which improved the HadAM3 simulations, are shown in Fig. 1c and d. Compared with the RCMs' simulations with 50-km resolution and HadAM3, the high resolution JMA MRI GCM did not yield a clear advantage in this West African monsoon simulation (Fig. 1), suggesting that the resolution probably is not the only factor with which the RCMs may have the advantage over coarse resolution GCMs. Through discussing the RCM dynamic downscaling ability, this review should provide more information on the possible advantage of RCMs over GCMs, such as treatment in physical processes, in regional climate studies.

Part of the difficulty in exploring the dynamic downscaling ability issue is rooted in the lack of validation data for small scale features (e.g., Leung et al., 2003a). Simply applying low resolution global reanalyses as climate reference for comparison is inadequate because the small scale features are absent in the global reanalyses. Because of this data issue, Denis et al. (2002) adopted the “Big Brother” approach, in which a large-domain regional high resolution model was used to produce a high resolution reference dataset for evaluation as well as a low resolution dataset after filtering high frequency information. This filtered data set is then used to drive a nested RCM with the same dynamic and physical processes over a small domain. Whether the nested RCM could regenerate those filtered fine resolution features would be used as a criterion to assess the RCM's dynamic downscaling ability. Although this approach seems to solve the issue of high resolution validation data, the nested RCM, however, only produces the features in the driving model with the same dynamic and physical processes, which does not necessarily represent the real world. The RCM's dynamic downscaling will eventually be judged by its ability to produce realistic simulations/predictions. As a matter of fact, from the beginning of the operational weather forecasting, the limited area models were intended to generate better prediction of some rather large scale phenomena, such as precipitation, than the imposed GCM products with, in most cases, different dynamics and physics. Ideally, high resolution observational data and/or regional reanalysis data should be used to assess the RCM's dynamic downscaling ability. However, in many cases those data are still unavailable. To further investigate the usefulness of the dynamic downscaling, Shukla and Lettenmaier (2013) conducted the statistical downscaling first to the coarse resolution data that is used for LBC and then compared the results between statistical downscaling and dynamic downscaling with the reference data. This approach more adequately assesses the value of

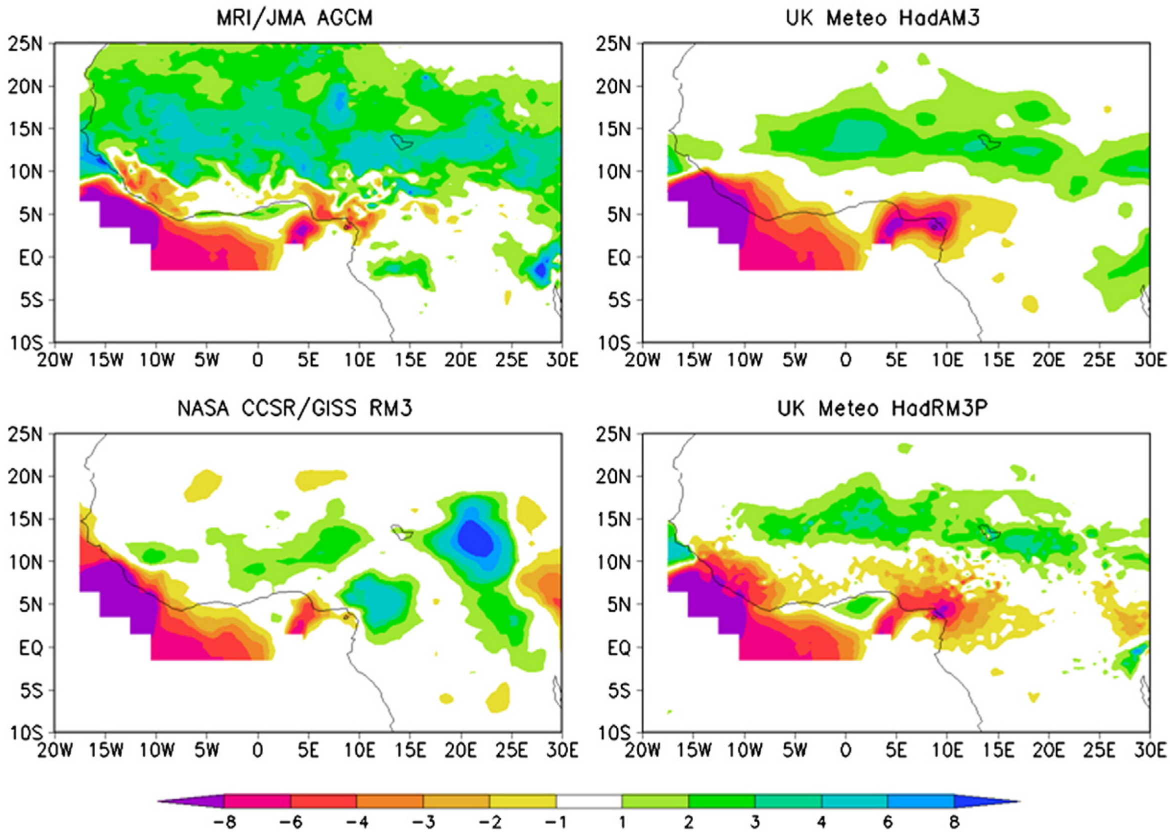


Fig. 1. Simulated JJAS precipitation biases: (a) MRI GCM, (b) HadAM3 GCM, (c) RM3 RCM, (d) PRECIS RCM. Unit: mm day^{-1}. Modified based on Druyan et al., 2010 and Xue et al., 2010a.

dynamic downscaling because statistical downscaling requires much less resources.

On other hand, some studies only use observational data for comparison to demonstrate dynamic downscaling ability, which is not sufficient. The improvement after dynamic downscaling over the data used for LBCs is also important for examining the dynamic downscaling ability. Due to lack of data and lack of established procedures for assessing the dynamic downscaling ability, in quite a number of studies that are reviewed in this paper, only results from sensitivity experiments are presented. Those studies only demonstrate the sensitivity of dynamic downscaling ability to certain factors/processes, and do not necessarily mean that they can add value to dynamic downscaling. We include these studies in this review paper, however, because the dynamic downscaling issue has not been comprehensively investigated and we wish that this review stimulates more investigation with proper data for evaluation and methods to explore whether these factors really help improve dynamic downscaling ability.

In this review paper, we will present several factors that have consistently demonstrated strong impact on the dynamic downscaling ability, such as imposed LBCs, domain size, and horizontal resolution, as well as physical processes, such as convective scheme and vegetation and soil processes. Most RCM results presented in this paper were obtained using one-way nesting, i.e., the RCM has no feedback to the GCM. There are few papers studying the two-way nesting issues (e.g., Chen et al., 2010), but we will not cover the two-way nesting experiments here.

2. Lateral boundary conditions (LBC)

2.1. LBC Quality

Because RCMs are driven by LBCs and their simulations are also affected by the initial conditions, the impact of LBCs and initial conditions on dynamic downscaling is the primary issue in dynamic downscaling studies and the natural approach is to select the "best" data as LBCs (e.g., Jacob and Podzun, 1997; Racherla et al., 2012). Although there are numerous tests with different reanalysis data, which are considered as better LBCs compared to those produced by GCMs, there is no single reanalysis data set yielding the best results in every region and/or every season. For example, in an East Asian summer monsoon study (Yang et al., 2012b), the Weather Research and Forecast (WRF) model with the ARW dynamics core forced by three reanalysis datasets (NCEP-R2, Kanamitsu et al., 2002; ERA-40, Uppala et al., 2005; and JRA-25, Onogi et al., 2007) showed remarkably different results in summer seasonal mean precipitation and geopotential height at 850 hPa, primarily caused by differences in the lateral boundary moisture fluxes over the Bay of Bengal and the Philippine Sea. Only the ensemble mean of NCEP-R2, ERA-40, and JRA-25 as LBCs considerably reduced the biases in the model simulation.

Significant differences in reanalysis moisture fields are reported in another study with a more systematic evaluation of the quality of the reanalysis data sets (Brands et al., 2012), which assessed the similarity of middle-tropospheric variables from 40-year ERA-40 and NCEP–NCAR reanalysis data on a daily time scale. For estimating the spatial dissimilarity, different statistical methods were employed. Fig. 2 displays the spatial differences between ERA-40 and NCEP/NCAR reanalysis 1 for all June–July–August (JJA) and December–January–February (DJF) days between 1980 and 2000. Dissimilarities are measured by the statistic of the two-sample Kolmogorov Smirnov Test (KS-statistic). Grid boxes with spurious distributional differences (alpha = 0.05) are whitened. The p-value of the KS-statistic is calculated upon the effective sample size of the daily time series (which are serially correlated). In this global similarity maps for each variable under study, it was found that significant dissimilarities for specific humidity existed in many regions of the world, especially over the tropical and subtropical oceans. Those discoveries are consistent with Yang et al.'s results (2012b). Moreover, these differences not only occurred in the mean, but also in higher-order moments.

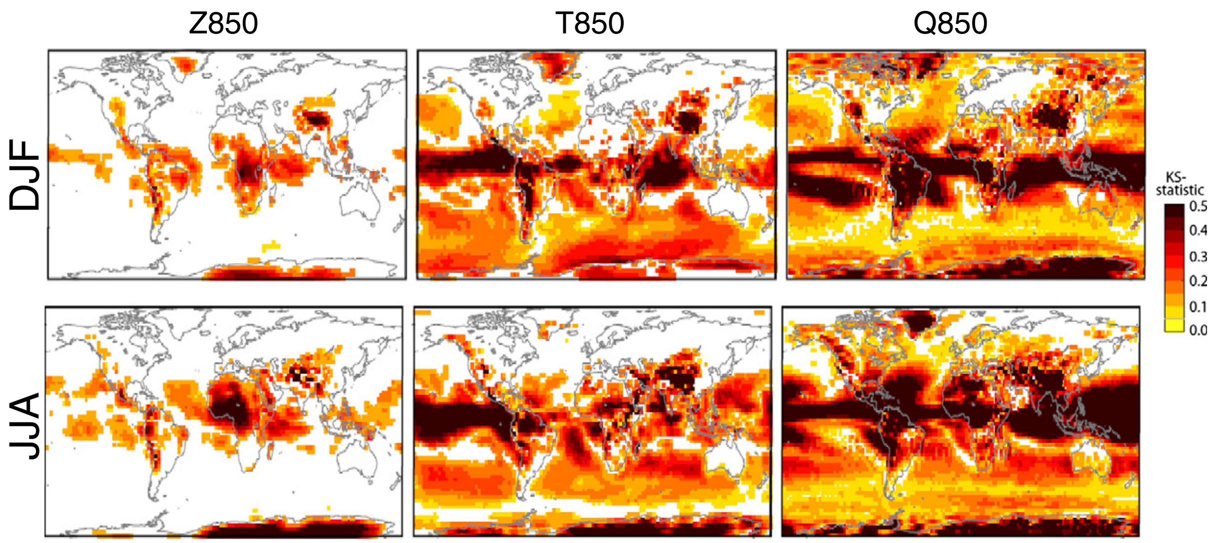


Fig. 2. Maps of distributional similarity for the daily time series of ERA-40 and NCEP–NCAR Z, T, and Q in DJF (top panel) and JJA (bottom) at 850 hPa. Color darkening from yellow to black indicates increasing dissimilarity. Grid boxes with spurious distributional differences are whitened. Modified based on Brands et al. (2012).

Since the reanalysis data normally consist of bias, anomaly nesting has been introduced for LBC coupling (Juang and Kanamitsu, 1994). However, a North American monsoon study revealed that the bias corrections associated with anomaly nesting should be used with caution. For instance, it may not be appropriate to correct monthly and diurnal variability errors when the correction is applied to the seasonal average (Chan and Misra, 2011).

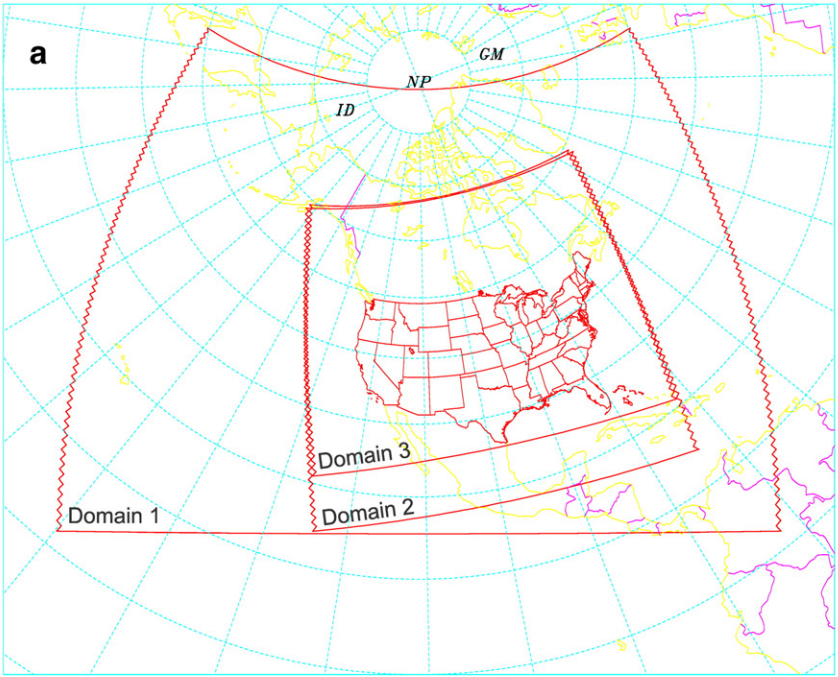
The regional reanalysis data, such as the NCEP North American Regional Reanalysis (NARR, Mesinger et al., 2006), which provides products with higher resolution and better data quality, have recently been applied for dynamic downscaling. A North American regional dynamic downscaling study (Xue et al., 2007) shows that although the RCM's simulation with NARR as LBCs clearly showed better results in monthly and seasonal means of precipitation and power spectrums of precipitation and total kinetic energy compared with those using the global reanalysis, Reanalysis II (Kanamitsu et al., 2002), the RCM actually failed to add value in precipitation after downscaling compared with NARR, which may imply a limit of dynamic downscaling. No data are available to assess the downscaling ability for other atmospheric fields when NARR is used as LBC since the NARR has been considered as the best "real" data with the highest resolution. In a "Big Brother" type of North American regional winter season study focusing on precipitation, specific humidity, and zonal wind (Diaconescu and Laprise, 2013), it is found that if an RCM is driven by a relatively high resolution GCM (Big Brother) with small errors, no improvement is found at the large scales simulated by the RCM. The added value will be solely in the RCM-simulated small scales that are not present in the driving GCM fields. If an RCM is driven by a very low resolution GCM (Big Brother) presenting large errors, then important reduction of errors at large scales is sometimes possible when the domain is sufficient large. High resolution RCMs appear to have some skill at recovering part of the amplitude deficient patterns, in both the stationary and the transient components. When the GCMs are applied for LBC, although high resolution input probably is preferred (e.g., Dimitrijevic and Laprise, 2005), some studies (e.g., Amengual et al., 2007) show that there is no clear benefit in using a high resolution GCM as LBCs when large errors are present in the GCM.

2.2. LBC coupling

In addition to LBC data selection, the coupling of an RCM and the LBCs can also be an important issue in dynamic downscaling. Different RCMs have different coupling strategies and numerical approaches. In the Eta model and NCEP's WRF/NMM dynamical core (Janjic et al., 2001, 2010; Janjic, 2003), the values of atmospheric variables along the 2nd outermost line of grid points ("inner boundary") are defined as horizontal four-point averages, thus being an average of the prescribed or extrapolated values on the outermost line and values on the third outermost line of points, which are fully predicted (Mesinger and Janjic, 1974; Mesinger, 1977). Probably more important than the four-point averaging for dynamic downscaling is that a simple first order upstream semi-Lagrangian scheme is used in three rows along the boundaries starting from the third outermost line (e.g. Janjic et al., 2010). In addition to taking care about well-posedness of the advection process, the upstream advection scheme heavily damps small scale noise in this transitional area between the boundaries and the interior of the domain. In many other RCMs, the relaxation and diffusive boundary condition terms are gradually applied to several outermost grid point rows; i.e., using a weighting function to the prescribed LBC that is equal to one at the border of the domain and linearly decreasing to zero at the most inner grid point (e.g., Davis, 1976; Anthes et al., 1987). To avoid sharp transition from the model solution to the driving boundary fields and to reduce the noise produced by the LBCs, a buffer zone of at least 10 grid points is commonly used in many RCMs, and large domains may require broader buffer zones (e.g., Giorgi and Mearns, 1999). Zhong et al. (2010) investigated the effects of buffer zone size on regional climate simulation by performing a number of experiments using RegCM3 with the buffer zone size expanding outward, i.e., keeping the internal domain size the same, to study an abnormal flooding event in China in summer of 1998. They found that a broader buffer zone is only favorable to low frequency (large scale) circulation systems in the upper troposphere, and that it is not effective in reproducing circulations in the middle and lower troposphere and the precipitation distribution. They speculate that physical processes seem more important than the buffer zone size for reproducing the details of precipitation.

2.3. Re-initialization and LBC coupling interval

The sensitivity of the RCM's dynamic downscaling behavior to re-initialization and/or the coupling time interval with LBC is another issue under extensive investigation. There is no rule that limits an RCM's multi-initializations. Due to the limitation of RCMs' downscaling ability, some studies have applied multiple initializations but still examined the climate statistics, such as monthly and seasonal means. Studies indicate that when the LBC data have good quality, more frequent re-initialization and/or frequent coupling with LBCs should help the RCM dynamic downscaling ability (e.g., Lucas-Picher et al., 2013; Antic et al., 2006; Gao et al., 2007; Di Luca et al., 2012). Fig. 3b shows that when the RCM is initialized only once during the three-month integration, the simulated area-averaged precipitation with Domain 1 (Fig. 3a) dries out after 30 days (Xue et al., 2007). However, when the model was reinitialized once a day, such behavior does not appear with the same domain size (Xue et al., 2001). Lo et al. (2008) also found similar behavior for monthly mean precipitation and atmospheric variables in a one-year integration. In their tests, a run with a more frequent (e.g., weekly) re-initialization outperforms that with less frequent re-initialization (e.g., monthly). The shortcoming of frequent updating is that the surface hydrology variables, such as soil moisture and runoff, cannot be properly produced because they need much longer spin-up time. Meanwhile, there seem to be optimal coupling time intervals for different RCMs. For instance, Dimitrijevic and Laprise (2005) found little improvement in summer simulations of precipitation, surface temperature, sea level pressure, and 500-hPa vorticity field by reducing the LBC input time interval from 6 h to 3 h with the Canadian RCM. Fang et al. (2010) found that a coupling interval of 3, 6, or 12 h tended to produce more successful simulations of precipitation, surface temperature, and



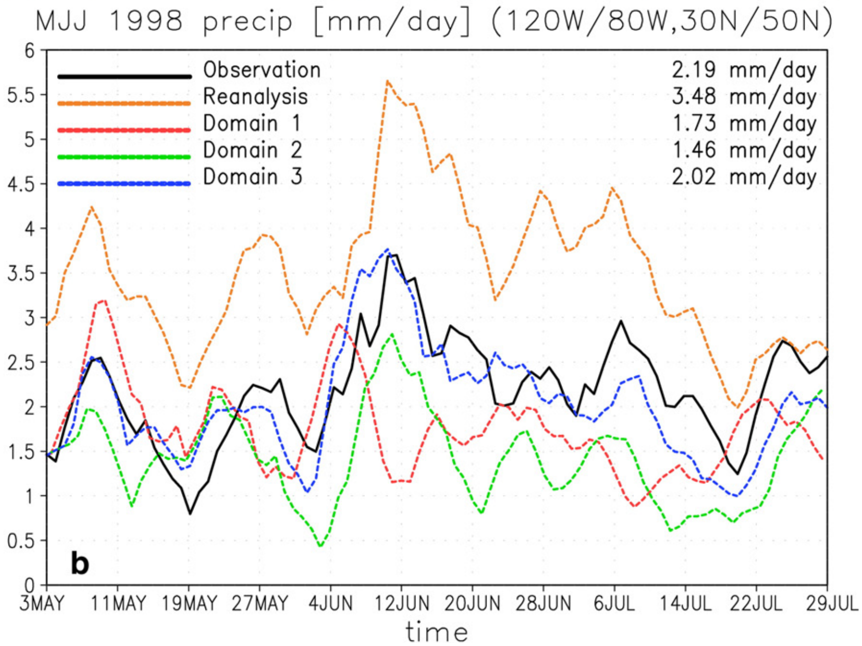


Fig. 3. (a) RCM domains, and (b) comparison of time series of observed and reanalysis precipitation and simulated precipitation with different domains. Unit: mm day^{-1}. Modified based on Xue et al., 2007.

SST than if using 1 or 24 h for the Regional Integrated Environment Model System (RIEMS).

In the RCM studies, the spectral nudging and/or LBC bias correction has also been applied to reduce RCMs' internal variability and/or departures between driving, i.e. LBCs, and driven fields (e.g., Davis and Turner, 1977; von Storch et al., 2000; Kanamaru and Kanamitsu, 2007; Cha et al., 2011; Xu and Yang, 2012; Yoshimura and Kanamitsu, 2013; Omrani et al., 2013; and numerous others). Because this approach substantially changes the RCM's internal variability and affects every factor/process that we review here, a comprehensive discussion on this issue is out of the scope of this paper. We do not discuss this method here.

2.4. LBCs in sensitivity/impact study

RCMs have been widely used for sensitivity studies to test how sensitive the model is to certain variable changes, such as soil moisture, and to some events, such as the impact of aerosol deposition on snow cover. In almost every RCM sensitivity study so far, the same LBCs are used for both control and anomaly runs, in which the tested variables, such as soil moisture, are changed from the control run. As discussed in the Introduction, the RCMs are designed to preserve the large scale circulation features in imposed LBCs and to add more information at different, especially finer, scales. The same LBC would hamper the development of the perturbation produced in the anomaly run because the imposed LBC tries to reinstall the climate in the control run. In a recent study (Xue et al., 2012), which explored the impact of spring subsurface soil temperature (SUBT) anomaly in the Western U.S. on Southern Great Plain summer precipitation using the Eta model, it was found that the SUBT effect on the Southern U.S. precipitation is through Rossby wave eastward propagation in westerly mean flow. In addition, the steering flow also contributed to the dissipation of perturbation in the northeastern U.S. and its enhancement in southeastern U.S. The adequate Eta results for the SUBT anomaly, which were compatible with the observed anomaly, however, were obtained only when the Eta model's control or anomaly run was driven by the corresponding GCM's control or anomaly run, respectively; i.e., the GCM control run and anomaly run were conducted first, then their results were used for the RCM control and anomaly runs' LBC, respectively. When the same reanalysis data were applied for both (control and anomaly) Eta runs' LBCs, the observed precipitation anomalies could not be properly produced (See Fig. 7 in Xue et al., 2012).

In some cases, the anomaly run in the sensitivity study produces a strong local perturbation, which generates strong anomaly signals despite the inconsistencies caused by the same LBCs. However, when the main pathway for the perturbation developing is through modified large scale circulation, the imposition of the same LBCs seems to hamper the necessary modification in the anomaly run at large scales, especially when the anomaly forcing is not that strong. Therefore, we believe that it is necessary to introduce the "anomaly downscaling" concept, in which the focus is on how the anomalies in the GCMs are downscaled in the RCM's control and anomaly runs. This issue should be comprehensively studied since more and more RCM applications are used for impact studies with different scenarios, such as land use land cover changes.

3. Domain size, domain position, and resolution

Domain size and domain position significantly affect dynamic downscaling ability for precipitation and atmospheric variables (e.g., Jacob and Podzun, 1997; Vannitsem and Chomé, 2005; Alexandru et al., 2007). When the domain size becomes big, the internal variability of the model also becomes large, such that there is more possibility for an RCM to drift away from the LBCs' climatology. Fig. 3a shows three Eta RCM domains over North America and Fig. 3b shows the time series of precipitation produced by these three domains. With the big domain (Domain 1 in Fig. 3a), the ensemble mean (consisting of five cases) was able to produce the observed daily precipitation averaged over the U.S. well only during the first 10 days (Fig. 3b), after which the simulated time series of precipitation showed a significant dry bias and failed to capture the major weather events during the three-month simulation (Xue et al., 2007). Only when the domain size gets relatively smaller (Domain 3 in Fig. 3a), the RCM is able to capture the observed precipitation variability. This discovery has also been confirmed by Bhaskaran et al. (2012) in their Indian monsoon study using the HadRM3P, which has a buffer zone with a width of eight horizontal grids, in a 13-year simulation. The seasonal mean hydrological cycle and intraseasonal variability of precipitation are the subjects in this study for investigation. In addition, they also notice that different subdomains may need different optimal domain sizes.

However, when the domain size is too small, the LBCs may be too dominant, such that it is hard for the RCM to correct some improper large scale features inherited from the LBCs and to produce adequate small scale features through interactions. It has been found that sufficiently large domain size and fine enough resolution were needed to simulate the essential features of precipitation in the South Asian tropical and monsoonal region (Leduc and Laprise, 2009). This study also found that the larger the domain, the more transient-eddy spectral variance could be produced; within the physical domain, this added variance corresponds to the small scale features that do not exist in the large scale flow driving the RCM through the LBCs. There is a characteristic distance that the large scale flow needs to travel before developing small scale features. Improper small domain size would especially hamper the full development of local interaction in sensitivity studies. For example, Seth and Giorgi (1998) found that using a larger domain they produced positive feedback for soil moisture effects, which were consistent with most soil moisture/atmosphere interaction studies. The opposite feedback was produced when the domain size was small (Giorgi et al., 1996).

In addition to the domain size, the domain boundary positions can also substantially affect the results. For example, Giorgi et al. (1996) placed the left boundary over the U.S. Pacific coastal waters to avoid complex topography within the boundary zone. Liang et al. (2001) used the locations of the upper-level jet stream and low level jet to determine the positions of northern and southern boundaries. Xue et al. (2007) found that for the U.S. summer, the southern boundary in the Gulf of Mexico and Caribbean Sea is most relevant when Reanalysis II was used as LBCs. Fig. 3a shows that the main difference between Domain 2 and Domain 3 are southern boundary location; the model with Domain 3 showed much better dynamic downscaling ability for the precipitation than the model with Domain 2, whose southern boundary was located in the Caribbean Sea and whose results showed a serious dry bias. In fact, the southern boundary area in Domain 2 was identified as having the largest discrepancies between different reanalyses (Fig. 2. Brands et al., 2012). Studies with other regions also suggest that LBCs should avoid regions with large uncertainty in reanalyses. For instance, in an East Asian study, Gao et al. (2011) found that to improve dynamic downscaling, the western boundary position in East Asia should avoid the Tibetan Plateau, which was also a region associated with high uncertainty in Fig. 2.

One of the advantages of the RCM over the GCM is its high resolution. In general, the high resolution RCM produces better results than the GCM-produced LBCs (e.g., Qian and Zubair, 2010; De Sales and Xue, 2011; Caron et al., 2011). However, such comparison may be misleading because the improvement could be due to the better dynamic or physical treatments in the RCMs. Using a model with the flexibility to configure the horizontal meshing such that it can be run in both limited or global area extent, Caron et al. (2011) found a clear improvement in the realism of Atlantic tropical cyclone activity when comparing the resolution increased from 2° using the global area extent to 0.3° resolution using the limited domain. Moreover, Hagos et al. (2013) also found that when they increased their RCM's resolution from 1° to 0.2° and the nested second domain resolution from 0.2° to 0.04°, the effect of moisture transport by eddy fluxes could be better simulated in their idealized regional aquaplanet simulations. Xue et al. (2007) found that among different resolution and domain size tests, only the RCM with 32-km resolution (the smallest in their experiments) in conjunction with appropriate domain sizes was able to properly simulate precipitation and other atmospheric variables, especially humidity, over the southeastern U.S. during all three-summer months and to produce a better spectral power distribution than the data used for LBCs. In another study covering the European Alpine region, compared to the 10-km parent simulations, the convection permitting climate simulations with 3-km grid spacing improved summertime precipitation diurnal cycles, produced better extreme precipitation intensities and more accurate distribution of rain, and improved precipitation (Prein et al., 2013). However, in a study of daily precipitation events over the southern United Kingdom, Chan et al. (2013) found that although increasing resolution (especially from 50 to 12 km) improved the representation of orographic precipitation in general, they did not see any clear evidence that the 1.5-km simulation is superior to the 12-km simulation at the daily level.

4. Physical processes I: convective precipitation processes

A number of studies have identified cumulus parameterizations as a crucial factor significantly affecting dynamic downscaling ability. Most of them focus on testing different convective parameterizations in RCMs. Among those schemes, the Grell scheme (Grell et al., 1994; Grell and Devenyi, 2002), which was originally based on Arakawa and Schubert (1974); the BMJ scheme (Betts and Miller, 1986; Janjic, 1994); and the KF scheme (Kain and Fritsch, 1993; Kain, 2004), which was developed from Fritsch and Chappell (1980); have been tested more extensively. All these studies intended to evaluate convective schemes' performance in their case studies in certain regions. For instance, using RegCM, Giorgi and Shields (1999) showed that the Grell Scheme produces an overall more realistic regional climate over the continental United States. Liang et al. (2004) reported that although KF has demonstrated superiority in North American regional climate studies, the Grell scheme has its own compelling advantages over certain regions, such as the Atlantic Ocean and the Midwest, and over certain aspects, such as the diurnal cycle over the Great Plains. Zhu and Liang (2007) noticed that the dominant empirical orthogonal function (EOF) mode of the U.S. summer precipitation interannual variation, identified with the out-of-phase relationship between the Midwest and Southeast in observations, is reproduced more accurately by the Grell than the KF scheme, which largely underestimates the variation in the Midwest. The second EOF pattern, which describes the consistent variation over the southern part of the Midwest and the South in observations, is captured better by the KF scheme than the Grell, whose pattern systematically shifts southward. Using MM5, Gochis et al. (2002) in a 1999 North American monsoon (NAM) case found that the KF scheme produces better vertical thermodynamic structures and hence more realistic convective precipitation associated with NAM. However, this result seems unsupported by Xu and Small's study (2002) on NAM intraseasonal and interannual variability also using MM5, which found that the Grell–RRTM simulation produces the most realistic patterns and magnitudes of rainfall, including intraseasonal variations and the differences between wet and dry years. Over South Africa, Ratna et al. (2013) indicated that in WRF/ARW, the BMJ scheme seemed to reproduce the intensity of rainfall anomalies and also exhibited the highest correlation with observed interannual summer rainfall variability there compared with other schemes. Due to the development of the new general mesoscale forecast models, such as WRF, which consist of broad selections of different physical parameterizations, studies have combined different cumulus schemes, radiation schemes, and planetary boundary layer (PBL) schemes in an attempt to define the optimal combination of physical parameterizations for certain regional climate studies (e.g., Xu and Small, 2002; Leung et al., 2003b; Lynn et al., 2010; Flaounas et al., 2011; Solman and Pessacg, 2012; Yuan et al., 2012). Using MM5, Solman and Pessacg (2012) found that based on model performance in sea level pressure, surface temperature, and precipitation simulation from October through November, no single combination was found to perform the best over the entire domain and during their entire integration period for their La Plata Basin study. Flaounas et al. (2011) found that the PBLs seem to have the strongest effect on the vertical distributions of temperature and humidity, and rainfall amount, and convective schemes strongly influence precipitation variability in their WRF/ARW simulations for the year 2006 West African Monsoon simulation.

Efforts have been made to further examine the mechanisms behind the discrepancies using different schemes. For example, Liang et al. (2004) noticed that the KF scheme incorporates detailed cloud microphysics and entrainment and detrainment between clouds and environment, which are absent in the Grell scheme. When convection is triggered, the KF scheme removes all Convective Available Potential Energy (CAPE) within the relaxation time, whereas the Grell scheme adjusts the buoyancy toward an equilibrium state depending on the strength of cloud-base vertical motion. The rainfall is parameterized as the product of precipitation efficiency with integrated water vapor and liquid flux about 150 hPa above the lifting condensation level in the KF scheme, but with total condensate and cloud-base mass flux in the updraft for the Grell scheme. Liang et al. (2004) did not further examine whether and which processes in the schemes produce the simulated differences among these two schemes. In another study, Yang et al. (2012a) tested five key parameters in the latest KF scheme related to the downdraft mass flux rate, starting height of downdraft above the Updraft Source Layer, environmental entrainment mass flux rate, turbulent kinetic energy (TKE) in the sub-cloud layer, and the consumption time of CAPE, over the Southern Great Plains in a June 2007simulation using the WRF/ARW. The results show that the model bias for daily precipitation can be significantly reduced by using five optimal parameters, especially for heavy precipitation. The simulated precipitation and other model variables were more sensitive to the changes of downdraft- and entrainment-related parameters and consumption time of CAPE than to the other two parameters.

It should be pointed out that these convective parameterizations were initially designed for weather forecasting. Generally, the needs from convective parameterization overlap a lot for weather and regional climate applications. In weather forecasting there may be more emphasis on the timing of convection and its intensity, while long RCM runs may expose issues of mean behavior over tropical oceans for example for schemes that are mostly developed for continental rainfall prediction. Some of the parameterizations that are good at specific weather events may not 'score' well in a 'climate' sense because they deal with different temporal scales. Convective schemes can be retuned for different resolutions and convective regimes, such that the same scheme can behave differently even in the same region. Furthermore, the schemes are often updated, so that results obtained in one test a few years ago may not be valid any more. It is very likely that different versions of the same scheme are used in different studies. Therefore, it is questionable whether such comparison to select the best package is meaningful when simply extending a parameterization for weather forecasting scale and making assessment based on simulation at much longer temporal scales. Whether this is the best way to optimize physical package should be further investigated. It is always advisable, and generally done, to test long term behavior of weather-application-produced convective schemes.

We find that significant improvement in dynamic downscaling can be achieved by properly adjusting convective parameterizations for the dynamic downscaling region and resolution used. Fig. 4c shows that WRF–NMM with the BMJ scheme produces extreme high convective precipitation over the ocean near the West African coast. Although the BMJ convective scheme works well at mid-latitudes, it seems that due to abundant moisture supply over the warm tropical ocean, low level convergence produces convection and latent heat release and further enhances the convergence, producing a positive feedback. We made several changes in the BMJ convection scheme for this region, including the addition of dry air entrainment during parcel ascent and the modification of entropy calculation. We also reduced the values of dry saturated pressure deficit (DSP) at the cloud base, freezing level, and cloud top, which were used to generate humidity reference profiles of DSP over water, in an attempt to reduce deep convection over the ocean. Fig. 4d shows significant improvement in the precipitation simulation over ocean. This and Yang et al.'s study (2012b) all show that proper modifications of parameter(s) may

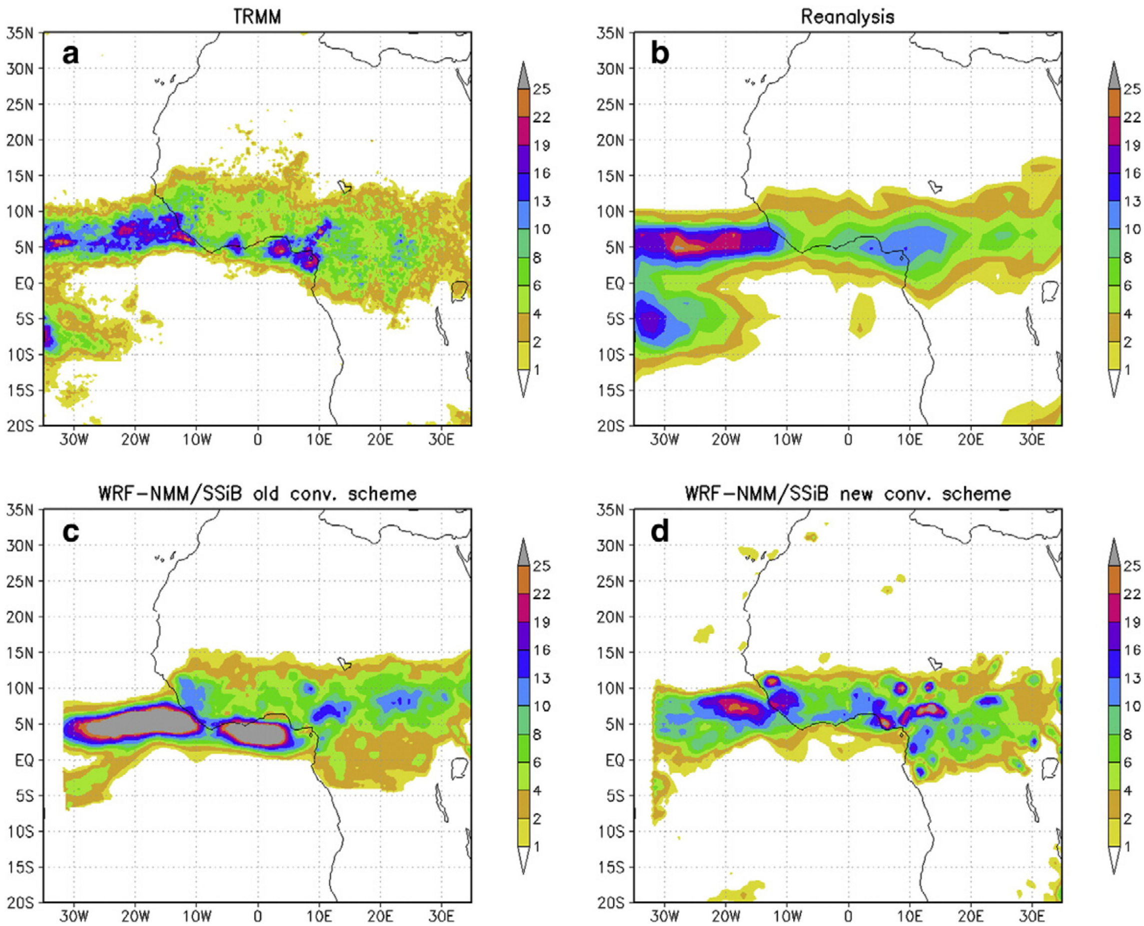


Fig. 4. Comparison of TRIM (a), reanalysis (b), and WRF/NMM simulated June 2000 precipitation (mm day^{-1}). The results from original and modified convective schemes are shown in (c) and (d), respectively.

be necessary when extending these convection schemes to long time studies and applying RCMs for different climate zones and with different resolutions, which could be one of the advantages of RCMs over GCMs, where a single parameterization set-up is commonly used in their global domain so far.

5 . Physical processes II: land surface processes

5.1. Land surface parameterizations

In addition to the topographic effect, studies have also demonstrated that vegetation and soil processes play a crucial role in dynamic downscaling. They have been listed as one of the major sources to generate small scale features in RCMs (Denis et al., 2002). Although at intraseasonal and seasonal scales, oceanic forcing may be the main source of climate variability over many regions, in places where land–atmosphere coupling is strong (Koster et al., 2006; Xue et al., 2004, 2006, 2010b), soil moisture and vegetation biophysical processes could make significant contributions to dynamic downscaling. Extreme climate events, such as droughts and flooding, are an important focus in RCM land/atmosphere interaction studies (e.g., Seth and Giorgi, 1998; Bosilovich and Sun, 1999; Zhang et al., 2003; Gao et al., 2011; Liu et al., 2013; Stefanon et al., 2013).

In a study on the 1993 U.S. flooding, by comparing the results from the Eta coupled with the SSiB biophysical model (Xue et al., 1991) with those from the Bucket model without explicit treatment of the vegetation biophysical process, the Eta/SSiB model produced more realistic monthly mean precipitation over the U.S. and the flood areas, better than the reanalysis that was used as LBCs (Xue et al., 2001). The improvements were mainly manifested in the intensity of the heavy rainfall. The changes were caused by different spatial distribution and diurnal cycle of surface latent and sensible heat fluxes between the Eta/SSiB and the Eta/Bucket simulations, leading to different boundary layer evolutions and atmospheric stability conditions, as well as low level moisture flux convergence in the heavy rainfall areas.

Another study on the 1998 Oklahoma-Texas drought with the NCEP Regional Spectral Model found that during April and May 1998, SST anomalies combined with a favorable atmospheric circulation to establish the drought. In June and August, the regional positive feedback associated with lower soil moisture/evaporation and precipitation contributed substantially to the maintenance of the drought (Hong and Kalnay, 2000). However, in another East Asian study, Kim and Hong (2007) found that the impact of soil moisture anomalies on the simulated summer rainfall in East Asia is not significant. A conflict between the local feedback of soil moisture and a change in circulations associated with the summertime monsoonal circulation in East Asia can be attributed as a reason for this result.

In a study exploring the mechanisms causing climate extremes in recent years in Europe, such as the unprecedented heat wave and serious drought in 2003 and cool summers with heavy precipitation and devastating floods occurring in 2002 and 2005 (Seneviratne et al., 2006), it was found that the increase in summer temperature variability predicted in Central and Eastern Europe is mainly due to feedbacks between soil moisture and the atmosphere. Stefanon et al. (2013) conducted sensitivity experiments for all heat wave episodes and found different soil moisture–temperature responses over low elevation plains, mountains, and coastal regions. Over the coastal regions, their results were consistent with Kim and Hong (2007).

In addition to local effects due to land processes, indirect effects due to remote soil subsurface temperature anomaly have also been explored in the RCM. An Eta model study (Xue et al., 2012) found that cold subsurface temperature anomalies over the Western U.S. high elevation areas during the spring could contribute to a June precipitation deficit over the Southern U.S. During the years with warm subsurface temperature anomaly, the anomalous cyclone induced by the surface heating produces the rainfall in the Southern U.S. When the subsurface had cold anomalies in the west, this mechanism no longer existed, which produced drought.

There is more evidence indicating that adequate soil moisture and vegetation presentations are crucial to dynamic downscaling. The WRF/Noah (Chen and Dudhia, 2001) with an interactive canopy model and a simple groundwater model (SIMGM) shows that incorporating interactive canopy and groundwater dynamics improves the simulation of summer precipitation in the Central United States and plays a significant role in enhancing the persistence of intraseasonal precipitation (Jiang et al., 2009). The enhanced model produces more precipitation in response to an increase in latent heat flux. The advantage of incorporating these two components into the model becomes more discernible after 1 month.

Snow water equivalent and snow cover were poorly presented in the current reanalysis model (e.g., Narapusetty and Molders, 2005; de Elia et al., 2008). Using the WRF/ARW, Waliser et al. (2011) found that a more realistic treatment of snow physics in a multi-layer snow model (Sun et al., 1999; Sun and Xue, 2001) could substantially improve snow-pack simulations in WRF compared with the single snow layer model, especially during spring when snow ablation is significant. Fig. 5 shows that the improvement in the WRF simulations of snow water equivalent and snow cover extent from the multi-layer snow model compared to a single layer snow model during the melting season. With only one layer snow in the WRF, the snow melting is substantially slow and the model produces unrealistic snow amount and large special distribution, similar to the reanalysis that imposes the LBC. There are many more studies exploring/evaluating the effect of different land surface parameterizations on RCM dynamic downscaling (e.g., Chen and Dudhia, 2001; Zeng et al., 2002, 2003; Jin and Miller, 2007; Singh et al., 2007; Alo and Wang, 2010; Barlage et al., 2010; Prabha et al., 2011; Sato and Xue, 2013) and identifying areas that are sensitive to the land/atmosphere interactions (e.g., Zhang et al., 2008). The studies presented above all provide useful information for improving RCMs' dynamic downscaling at intraseasonal and seasonal scales by improving the land representation in RCMs.

5.2. Specification of initial soil moisture and vegetation conditions

Because of the importance of land surface processes in regional dynamic downscaling, a number of studies have investigated the impact of specification of initial soil moisture and land conditions from data assimilation systems and satellite products (e.g., Pielke et al., 1997; Hong et al., 2009;

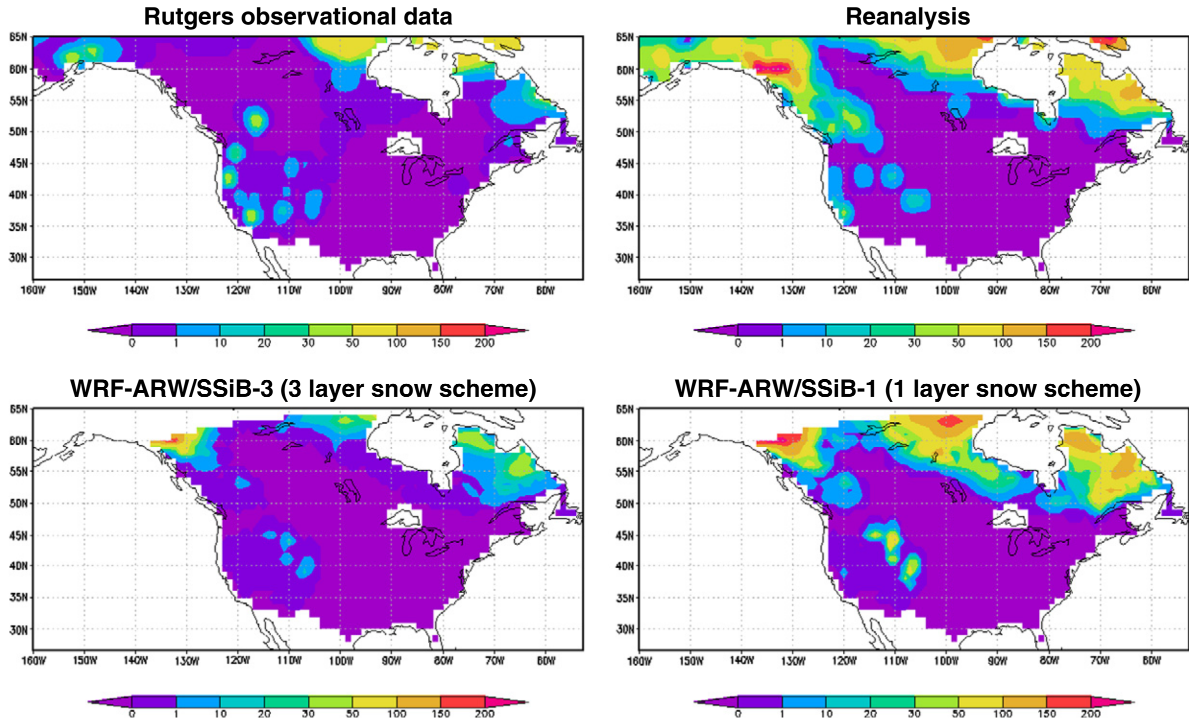


Fig. 5. Observed, reanalysis, and simulated May 1998 snow water equivalent (SWE) distributions.

Moufouma-Okia and Rowell, 2010; Sertel et al., 2010; Panegrossi et al., 2011). Using high resolution soil moisture data derived from ENVISAT/ASAR observations as the initial conditions for the MM5 simulation of the Tanaro flood event of April 2009, the ASAR-derived soil moisture field shows significantly drier conditions compared to the ECMWF analysis and significantly improved the simulation in timing of the onset of the precipitation, as well as the intensity of rainfall and the location of rain/no rain areas (Panegrossi et al., 2011). Hong et al. (2009) tested the WRF/ARW model using vegetation fraction derived from Moderate Resolution Imaging Spectroradiometer (MODIS) reflectance data with two different methods: linear and quadric. The model covers the NCAR Integrated Surface Flux Facilities area, most in the Southern Great Plains between eastern Kansas and the Oklahoma Panhandle. With both satellite products, they obtained improved results in sensible heat flux simulations in the eastern area and in latent heat flux simulations in the western and central areas.

Although there is consensus on the impact of initial soil moisture effect in dynamic downscaling, it remains an issue regarding which soil moisture data should be used for certain land models. For instance, it is well known that NARR produces better regional atmospheric features than the coarse resolution global reanalysis over North America. However, when the NARR soil moisture data were applied for the Eta/SSiB initialization, the results were worse than using the NCEP global reanalysis soil moisture data (Xue et al., 2007). The NARR used the Noah land model to generate the soil moisture, and NCEP global reanalysis uses a two layer soil model (Mahrt and Pan, 1984) to produce the soil moisture data. With the complex structure of the biophysical models, such as Noah and SSiB, the direct transfer of soil moisture produced from one biophysical model may not yield the optimal results when applied to another biophysical model. When using assimilated soil moisture data, which were derived also using the SSiB model, the WRF/SSiB produced the best downscaling ability (Sato and Xue, 2013). However, by and large, the differences caused by these two initial soil moisture data sets were not as substantial when compared with those produced by the effects of domain size, LBC, grid spacing, and different physical parameterizations based on the previously discussed studies.

5.3. Land–atmosphere coupling strategy

The discussions in Sections 5.1 and 5.2 have shown strong evidence that land surface processes play a significant role in dynamic downscaling by accounting for the exchange of energy and water between the land and the atmosphere. The study of Polcher et al. (1998) has suggested that a proper land–atmosphere coupling methodology is crucial for simulations of land–atmosphere interactions. Therefore, coupling of atmosphere and surface through PBL is an important issue in improving dynamic downscaling. However, the coupling problem remains largely unexplored due to complex processes involved across a range of scales and the technical difficulties in modify the land/atmosphere interface coding.

The key for a successful implementation of land surface processes into an atmospheric model is to ensure energy, water, and momentum conservation at the interface between the land surface and the atmospheric layers while solving the coupled transport equations (Polcher et al., 1998). The changes in temperature, humidity, and wind fields in the lower atmosphere and temperature and soil moisture at the surface should be consistent with the flux exchange between the interfaces. Although this principle is simple and well known, its realization is a rather difficult task. Because PBL schemes and radiation parameterizations are so different in different atmospheric models, it is necessary to design a specific approach to implement land models into an atmospheric model (e.g. Xue et al., 2001, 2004). Normally, the process includes modifications of both land surface and PBL schemes. However, when we implemented the SSiB into the WRF infrastructure, to make the WRF easy for different parameterizations to “plug” in, in the version that we provided for public release in NCAR, some interaction loops had to be simplified to avoid modifying the PBL schemes. While some of these processes only play secondary roles, some are more important.

For instance, in the WRF YSU PBL scheme (Hong et al., 2006), the friction velocity that is derived from the surface model is further modified in the PBL. When we implemented the SSiB into the WRF, since the calculations of surface turbulence fluxes were the important components in SSiB, the adjustment of friction velocity in PBL caused serious problems. Fig. 6 shows that with inconsistent friction velocity in the surface layer scheme and PBL, the simulated 200-mb zonal wind and precipitation (not shown) are substantially deteriorated, which suggests that the land/atmosphere coupling plays an important role in the large scale circulation in dynamic downscaling and deserves more attention in further dynamic downscaling studies.

6. Challenging issues

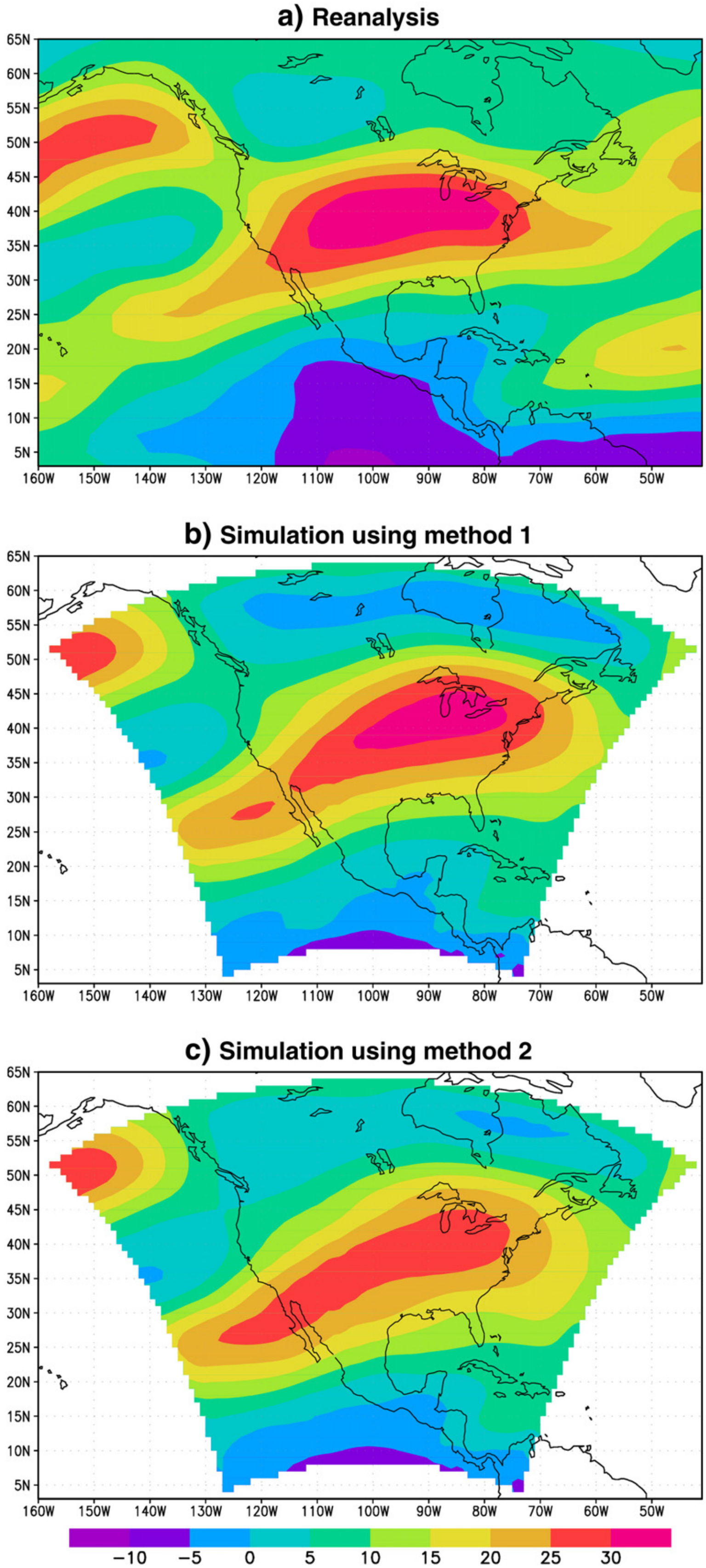
6.1. Downscaling ability for temporal variability

In previous sections, we mainly focused on the added values in spatial distribution and intensity. There is, however, very few results showing that the RCM dynamic downscaling adds value in temporal variability. For example, in the Multi-RCM Ensemble Downscaling of Multi-GCM seasonal forecasts (MRED) project, RCMs produced multi-member ensemble means of 22 winters (December to April) covering 1982 to 2003 over Part of North and Central America (from 124.75° to 60.0° W and from 24.75°N to 49.125°N with a 0.375° horizontal resolution). Compared with the NCEP Climate Forecast System (CFS) hind-prediction, which was used for MRED RCMs' LBCs, the UCLA–Eta RCM reduced the precipitation bias over the contiguous US land points from 1.6 in CFS to 0.0 mm day^{-1} and the root-mean-square-error from 1.9 to 0.6 mm day^{-1} based on GTS observations. However, little improvement was attained with downscaling in terms of precipitation temporal variability compared with CFS results. In fact, the RCM's precipitation time series are highly correlated with CFS' (the LBCs); for instance, in the Western and Eastern U.S., where the correlation coefficients of temporal variation of monthly mean precipitation between the CFS and Eta are about 0.97, both models' temporal correlation coefficients with observation are only about 0.45 (De Sales and Xue, 2013). Apparently inputs from LBCs every six hours impose great constraints on an RCM's temporal variability. This situation is quite consistent in many dynamic downscaling studies, in which SST was specified from the same data set as LBC data (e.g., Chou et al., 2002; Xue et al., 2007; Iizuka, 2010). Imposed LBCs in a fixed time interval greatly hamper the RCM's ability to add value in temporal variability. We will discuss this issue further in the section on Future Research Prospective.

6.2 . Future projection

The demands for future climate information at local-regional scales are huge, which has led to a dramatic increase in RCM simulations with increasingly higher resolution for future projections. However, based on the discussions in Sections 6.1 and 2.1, the RCM is very likely to mimic the imposed GCM LBC's trend and temporal variability, and the deficiency in GCM future prediction will be transferred to the RCM. Knutti et al (2010) have extensively discussed the challenges in combining projections from multiple GCM future predictions and concluded that extracting policy-relevant information is difficult. Among these challenges are that model skill in simulating present-day climate conditions is shown to relate only weakly to the magnitude of predicted change, and quantifying uncertainties from ensembles of climate models is difficult. The correlation between biases among the CMIP3 GCM is high, which makes averaging less effective at canceling errors. In addition, averaging model outputs may further lead to a loss of signal for extreme situations.

When the LBC quality deteriorates in future projections, the value of this exercise is controversial (Pielke and Wilby, 2012; Pielke, 2013; Mearns et al., 2013). A few studies have tackled this issue and mainly focused on surface temperature. Liang et al. (2008) found very high spatial pattern correlations of the RCM and GCM difference in surface temperature and precipitation between the present and future climate simulations, which suggests that major model deficiency in simulating present climate would be systematically propagated into future climate projections at regional scales. To reduce the GCM-related model dependence of future climate projections when using RCMs, correcting the biases in GCM-produced LBCs before running RCMs was proposed. In a RegCM4 study with three different sets of LBCs, which were generated with different interpolation methods, it was found that using different LBCs produced similar present-day summer rainfall patterns, but the predicted future changes differ significantly depending on how the LBC bias correction is treated (Yu and Wang, 2013). They claim that physical inconsistencies may be contained in the bias-corrected LBCs, increasing the uncertainties of RCM-produced future projections. Boberg and Christensen (2012), in a central Mediterranean study, demonstrate that projections of intense mean summer warming partly result from model deficiencies, and after correcting the biases, the Mediterranean summer temperature projections in an ensemble mean are reduced by up to one degree, on average by 10–20%. In another approach, McSweeney et al. (2012) demonstrated the importance of employing a well-considered sampling strategy to select GCMs used for LBCs based on Knutti et al. (2010) and others' recommendations. They first examine whether any GCMs should be eliminated for LBCs because of significant deficiencies in their simulation of current climate for that region. They then evaluate the range of the GCM future projections and identify models that best represent the full range of future climates, which will be used for the LBCs in future projections. Compared with numerous publications applying the dynamic downscaling with various applications of future projections, there are very few papers exploring dynamic downscaling ability in future projection. More extensive researches are required to close this gap (e.g., Chen et al., 2010; Rasmussen et al., 2011).


a) Reanalysis
b) Simulation using method 1
c) Simulation using method 2
65N
60N
55N
50N
45N
40N
35N
30N
25N
20N
15N
10N
5N
160W 150W 140W 130W 120W 110W 100W 90W 80W 70W 60W 50W
−10 −5 0 5 10 15 20 25 30

7. Discussions and future research prospects

LBCs are the driving force for RCMs and play the dominant role in dynamic downscaling. Because of this, Pielke and his colleagues have categorized dynamic downscaling into four typologies based on the types of imposed LBCs; i.e., from the analysis of observed data, reanalyses data, AGCM, or coupled AOGCM outputs; as well as downscaling purposes, i.e., for weather forecasting, seasonal simulation, or seasonal or climate prediction (Castro et al., 2005; Pielke and Wilby, 2012). When more variables in LBCs are specified based on model products rather than observation, the uncertainty in dynamic downscaling increases, which seriously impedes the RCM from adding information in its dynamic downscaling. The studies reviewed here suggest that RCMs have dynamic downscaling ability only under certain conditions, including adequate LBCs and proper domain setting, convective schemes, land surface parameterizations, initializations, and numerical schemes, as well as sufficiently large domains. Through interactions of these processes in the regional domain, the RCMs are able to provide added value compared with the data used for LBCs in some aspects (e.g., Mariotti et al., 2011; Xue et al., 2001, 2007; Liang et al., 2004; Seth et al., 2007; Solman and Pessacg, 2012). Any significant weaknesses in one of these aspects would cause an RCM to lose its dynamic downscaling ability. This is likely the reason why RCMs which have different convective and radiation schemes and land parameterizations in their models produce very different results compared with those with different parameterizations but only using only one single model (de Elia et al., 2008). To further understand the dynamic downscaling issue, in further dynamic downscaling research, the RCMs' results should not only be compared with observational data but should also be compared with the data used for specifying LBCs. Only comparisons between these three data sets can adequately show whether the RCMs really provide new information. In the following, we further discuss several issues important to dynamic downscaling but with less comprehensive investigation carried out so far.

7.1. Temporal variability and possible impact due to coupled ocean–atmosphere RCMs

Recently, fully coupled atmosphere–ocean RCMs have been used for dynamic downscaling studies (e.g., Aldrian et al., 2005; Ren and Qian, 2005; Seo et al., 2007; Artale, et al., 2010; Ratnam et al., 2013). In general, these studies reported an improvement in dynamic downscaling due to coupled models. For example, using the coupled RegCM3 and the ocean model ROMS, Ratnam et al. (2009) showed that the coupled model captured the main features of the Indian monsoon and simulated a substantially more realistic spatial distribution and monthly mean of monsoon rainfall compared to the uncoupled atmosphere-only model. A more striking feature is that in an East Asian summer monsoon (EASM) downscaling study (Yao and Zhang, 2009), using the coupled RegCM3 with specified SST the simulated correlation coefficients of the temporal variation of summer rainfall between the uncoupled model RegCM3 and observation were only 0.30 and 0.29 over the Yangtze River Valley and South China, respectively. The coefficients of the rainfall between the coupled RegCM3 and Princeton Ocean Model (POM) and observation are 0.48 and 0.61 over the Yangtze River Valley and South China, respectively, which is a substantial improvement. Another study (Liao and Zhang, 2013; Fang et al., 2010) showed that using the Regional Integrated Environment Model System (RIEMS, Fu et al., 2000) and the POM, the power spectrum of climatological intraseasonal oscillation of EASM rainfall is better simulated in the coupled model compared with the uncoupled model, especially the 30–60-day oscillations. The coupled model also showed greater skill than the uncoupled RIEMS in reproducing the principal features of climatological intraseasonal oscillation of EASM rainfall, including its dominant period, intensity, and northward propagation. These studies have shown promise with fully coupled ocean–atmosphere models to improve dynamic downscaling in temporal variability for some regions where the air–sea coupling is strong, such as East Asia, owing to the realistic phase relationship between the intraseasonal convection and the underlying SST resulting from the air–sea coupling. It is important to identify regions where ocean coupling plays an important role as done in land/air coupling study and to include the coupled ocean models in these regions' downscaling studies. Furthermore, dynamic vegetation processes have also recently been added to RCM downscaling. It is interesting to see whether these fully coupled surface/atmosphere systems will be adding value in temporal variability in certain regions.

7.2. Multi-model ensemble strategy

Due to deficiency in RCMs' dynamic downscaling ability, to provide scientifically credible information on regional climate and climate change, a multi-RCM approach has been taken (e.g., Druyan et al., 2010; Mearns et al., 2012; Kim et al., 2013). Shukla and Lettenmaier (2013) analyzed MRED multi-models' downscaling for seasonal hydrologic forecasting. They found that the MRED forecasts produce modest performance beyond what results from statistical downscaling of CFS. Although the improvement in hydrologic forecasting associated with the ensemble average of the MRED forecasts (Multi-model) relative to statistical downscaled CFS forecasts is significant for runoff and soil moisture forecasts with up to 3 months lead, the region of improvement is mainly limited to parts of the Northwest and North Central U.S.

It has been found that one or more RCMs outperform the other RCMs as well as the ensemble mean in Shukla and Lettenmaier's analyses (2013). Hence they argue that careful selection of RCMs (based on their hindcast skill over any given region) is critical for improving hydrologic forecasting using dynamical downscaling. Kim et al. (2013) evaluated 10 RCMs' downscaling performance for Africa covering 1989–2008 and found that for all variables, a multi-model ensemble (ENS) generally outperforms the individual models included in the ENS. However, they found that model biases vary systematically for regions, variables, and metrics, posing difficulties in defining a single representative index to measure model skill and for choosing ensemble members. These studies suggest that careful selection of the members with high dynamic

Fig. 6. Comparison of zonal wind (m s^{-1}) at 200 hPa. (a) Reanalysis, (b) latest simulation using Method 1, and (c) simulation using Method 2. Method 1 uses the same U* in SSiB and PBL schemes. Method 2 uses different U* in SSiB and PBL schemes.

downscaling ability for an ensemble mean is crucial to provide real and credible information.

These ensemble studies and the results presented in previous sections show that to improve dynamic downscaling ability, a simple increase of the number of ensemble members and/or trying the optimum combination of different parameterizations may not be a good approach, especially given that some schemes, such as convective parameterizations, were not designed for today's downscaling research. This review shows that using the RCM as a black box is very unlikely to achieve the dynamic downscaling goal and neither is a simple averaging of the results of multiple models or optimizing the combinations of different parameterizations. More rigid scientific analyses and better ensemble methodology need to be developed.

7.3. High resolution needs

With GCM grid sizes reducing and computer power increasing, the role of RCMs is now shifting to representing finer scales that still cannot be obtained with GCMs over long simulation times. The very fine resolution data is very useful for hydrological and other applications. RCMs are now starting to be run at convection-permitting scales, grid sizes less than 4 km, where cumulus parameterization can be replaced by explicit dynamics to represent deep convective systems. This reduces some of the parameterization uncertainty but increases the role of specifics in the microphysical schemes. Meanwhile, shallow convection still needs parameterization. Also 4 km grids may not be fully capable of resolving updrafts with smaller natural scales, as is found in the tropics for example. However, there are often significant gains in the timing and propagation characteristics of resolved convection.

Complex terrain offers another area where high resolution regional simulations will provide future benefit. Snow-pack climate studies (e.g. Rasmussen et al., 2011) require resolving high elevation areas, and grid sizes less than 5 km, while rainfall is also significantly modified by topography. RCMs will be an important tool for water resource studies while they may also be coupled to hydrology models for river flow and flood risk assessments.

Such RCMs are expensive to run for periods of years, and in climate simulations where GCMs are run a century, the RCMs may use a time-slice method driven by selected decades of GCM output to make them affordable.

Dynamic downscaling is a scientific field and more physical and dynamic-based approaches are extremely important, considering its broad applications. By and large, the research reviewed in this paper shows that substantial progress has been made during the past two decades in understanding dynamic downscaling; however, our understanding of the issue is still very limited and further comprehensive scientific research for the issues reviewed in this paper is warranted.

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