High-Resolution Late 21st-Century Projections of Regional Precipitation by Empirical Downscaling from Circulation Fields of the IPCC AR4 GCMs

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In a previous study, the authors described a methodology for statistical/empirical downscaling from low-resolution circulation fields to high-resolution regional precipitation. Empirical downscaling models (EDMs) were constructed using the relationship between variability in large-scale reanalysis predictor fields and observed monthly mean precipitation over four regions: the Southeast United States, the Upper Colorado River basin, China’s Jiangxi Province, and a portion of Central Europe. Here, these models are applied to predictor fields obtained from global climate models (GCMs) participating in the Coupled Model Intercomparison Project Phase 3 (CMIP3) to obtain alternate projections of precipitation changes between the late 20th and late 21st centuries. For three of the four regions, the annual cycle of precipitation for the late 20th century obtained from the ensemble average of the CMIP3 models using EDMs more closely matches observed precipitation than that obtained directly from the GCMs and for all regions the intermodel spread in the empirically downscaled climatology is substantially reduced. This supports the hypothesis that regional precipitation is primarily determined by large-scale circulation fields and that the latter are well-represented across the CMIP3 models. The EDMs are then used to calculate projected changes in the annual cycle of precipitation for the late 21st century due to global warming. Although the projected changes (1950-1999 to 2050-2099) are modest for both the raw and downscaled model results, the downscaled product shows much greater agreement across models, suggesting a greater confidence in projected
precipitation changes can be obtained efficiently using empirical downscaling.
1. Introduction

From the perspective of planning and adaptation, precipitation is one of the primary variables of interest in studies of potential changes in the climate system due to anthropogenic greenhouse warming because of its importance for water supply, agriculture, flood control, and ecosystems. Climatological precipitation varies on small spatial scales, especially in the presence of complex topography, that cannot be resolved by the present generation of global climate models (GCMs) such as those participating in the 3rd Coupled Model Intercomparison Project. Furthermore, these models display large biases in precipitation over many regions and the spread in projected future changes is often much larger than the ensemble mean change. As a way of circumventing these deficiencies, both dynamical and empirical/statistical downscaling approaches have been employed to generate precipitation projections at higher spatial resolution. Each of these approaches comes with a variety of advantages and disadvantages, which are discussed at length by Benestad et al. [2008] and Nicholas and Battisti [2011]. Perhaps the most compelling advantage of the empirical/statistical approach is computational efficiency, which makes the generation of large ensembles of projections a much more tractable proposition than it would be using a regional climate model (RCM).

In this study, the empirical/statistical downscaling approach described by Nicholas and Battisti [2011], and similar to that previously employed by Widmann et al. [2003] and Vimont et al. [2009], is applied to large-scale predictor fields obtained from the CMIP3 archive to produce ensemble projections of changes in the annual cycle of monthly mean precipitation between 1950-1999 and 2050-2099 as described in section 2. In section 3 we
show the results of ensemble projections for four regions — the U.S. Southeast, the Upper Colorado River basin, China’s Jiangxi Province, and Central Europe — and compare these with projected changes in precipitation from the GCMs themselves. Section 4 offers some concluding remarks on utility and implications of such projections.

2. Data and methods

Nicholas and Battisti [2011] describe a method for empirical downscaling of monthly-mean precipitation from large-scale predictor fields obtained from reanalysis. Briefly, the empirical downscaling model (EDM) is “trained” by regressing observed (in this case, high-resolution gridded) precipitation onto time variations in the leading patterns of large-scale predictor fields. By projecting the identified patterns onto an independent set of large-scale predictor fields and applying the associated regressions to the resulting timeseries, predictions of precipitation may be obtained at the resolution of the observed precipitation. Although a variety of methods can be used to identify the relevant patterns of large-scale variability, Nicholas and Battisti [2011] found that using standard empirical orthogonal function (EOF) analysis of predictor field combinations produced skillful results (in terms of replicating both the annual cycle and monthly anomalies) in cross-validation tests, often exceeding the skill of precipitation derived directly from reanalysis.

In this study, we apply the same method, generating EDMs of precipitation using monthly-mean predictor fields obtained from the NCEP-NCAR Reanalysis project (NNR [Kalnay et al., 1996]) and 0.5° gridded precipitation from the University of Delaware Terrestrial Precipitation dataset version 2.01 (UDel) for the period 1949-2008. The skill of the EDM is determined using cross-validation and the metrics described in Nicholas and
Battisti [2011], and is discussed briefly below. Next, hindcasts of 1950-1999 precipitation are generated by applying the EDMs to predictor fields obtained from 20th century commitment scenario (20c3m) runs of 18 models from the CMIP3 archive. Long-term monthly means are then calculated from each 600-month hindcast to obtain the annual cycle of precipitation for the period 1950-1999. The process is then repeated using output fields from A2 scenario (sresa2) runs of the same GCMs for the period 2050-2099 to obtain projections of the annual cycle of regional-scale precipitation during the latter half of the 21st century. In instances where a model had multiple runs available for a given scenario, EDM projections for all runs were averaged to produce a single estimate of the annual cycle of precipitation for that model and scenario. The GCM predictor fields were interpolated to same 2.5° grid as the NNR predictor fields prior to downscaling. For comparison with observations and EDM results, GCM precipitation is interpolated to the same 0.5° grid as UDel. In section 3, we show these hindcasts, along with projections of expected changes in the annual cycle of precipitation, for each model and each region for selected predictor-variable combinations.

Since this study is only concerned with the annual cycle of precipitation (and changes in it), standard forecast assessment metrics are unhelpful for quantifying the skill of our EDMs. In lieu of such measures, we the “annual cycle skill score” (ACSS) introduced by Nicholas and Battisti [2011]:

\[
ACSS = 1 - \sqrt{\frac{\sum_{i,j,k} \left[ \cos \theta_j \cdot (\hat{f}_{ijk} - \hat{x}_{ijk})^2 \right]}{\sum_{i,j,k} \left[ \cos \theta_j \cdot \hat{x}_{ijk}^2 \right]}}
\]

Here, the indices \(i, j, \) and \(k\) denote (respectively) times, latitude, and longitude in the forecast domain; \(\hat{f}_{ijk}\) is the forecast/hindcast local climatological mean precipitation for...
a given calendar month, $\hat{x}_{ijk}$ is the observed local climatological mean precipitation for a
given month, and $\theta_j$ is the latitude for each location. This measure is similar to the RMS
skill score (RMSSS [WMO, 2002]) except that it is weighted by the sum of the squares of
the climatological mean for each month and location. Thus, a given absolute error carries
a smaller penalty when true climatological monthly mean at that location is large. The
cosine term provides area weighting for each gridbox, although the domains used in this
study are sufficiently small that the inclusion of this term has little effect on the result.
The maximum value for ACSS is 1 for a “perfect” hindcast; ACSS may be negative and
there is no lower bound.

This procedure was used to downscale precipitation over four regions: interior Southeast
United States, the Upper Colorado River Basin in western Colorado and eastern Utah,
Jiangxi Province in southeastern China, and a portion of Central Europe including the
Czech Republic and parts of Germany, Poland, Austria, and Slovenia. To simplify the
analysis, only one predictor variable set is examined for each region; the predictor chosen
for each region was selected from among those described in Nicholas and Battisti [2011]
such that high levels of skill in replicating both monthly anomalies and the annual cycle
were achieved in cross-validation tests. Table 1 lists the predictor field sets, predictor
domains, and test domains for each downscaling region.

Ensemble convergence is quantified using a spread score, $S$, defined as the mean absolute
deviation from the ensemble mean projection for a particular month, averaged over all
months:

$$S = \frac{1}{12M} \sum_{i,m}^M |P_{m,i} - \bar{P}_i|$$
Here, $P_{m,i}$ is climatological projection for a particular model, $m$, and month, $i$; $\bar{P}_i$ is the ensemble mean climatological projection for a given month; and $M$ is the total number of ensemble members ($M = 18$ in the case of this study). Spread scores for all four regions are shown in Table 2.

3. Results

3.1. Southeast United States

Results for precipitation downscaling over the interior Southeast United States are shown in Figure 1. The predictor used is a combination of specific humidity, zonal wind, and meridional wind at 850 mb (Q850-U850-V850) and is interpreted as a measure of low-level moisture flux into the region. The top panel of Figure 1 shows the annual cycle precipitation produced by all 18 GCMs examined in this study (blue) and statistically downscaled using predictor fields from these same GCMs (red) for the period 1950-1999. In general the GCMs tend to underestimate precipitation throughout most of the year, with only two models showing the type of large summertime biases that Nicholas and Battisti [2011] found in NNR. The EDM results tend to hew more closely to the observed annual cycle from the GCMs (black), with an average ACSS of 0.795 compared with 0.683 for the GCMs. The middle panel shows projected 1950-1999 to 2050-2099 changes in the annual cycle of precipitation for the 9 most skillful GCMs and EDMs; the bottom panel shows these same changes represented as percentages of the observed monthly means for the period 1950-1999. Although the ensemble mean of the projected changes is similar for GCMs and EDMs, and generally small, there is considerably more spread in the direct
GCM projections, with some models showing decreases of up to 40% in certain months (see Table 2 and Figure 1).

### 3.2. Upper Colorado River Basin

Results for precipitation downscaling over the Upper Colorado River Basin are shown in Figure 2. The predictor used is a combination of specific humidity, temperature, and meridional wind at 700 mb (Q700-T700-V700). GCMs consistently overpredict precipitation in most months of the year for this region, with excesses typically in the range of 50-200%. The EDMs follow the observed annual cycle much more closely, albeit with notable deficits in the summer months, and show considerably less spread than the GCMs (Table 2 and top panel of Figure 2). The average ACSS for EDMs is 0.549 compared with −0.131 for the GCMs. Projected 1950-1999 to 2050-2099 changes for the 9 most skillful GCMs and EDMs (middle and bottom panels of Figure 2) have similar shapes, with EDM ensemble mean showing a smaller springtime reduction and a larger increase in the late summer through fall. The ensemble mean changes reach values of ±30% in some months and could have a serious impact on water resources for this region; however, both GCMs and (especially) EDMs show relatively small changes during the winter months, when snowpack is produced.

### 3.3. Jiangxi Province, China

Jiangxi Province, comprised primarily of the Gan River basin, lies just south of the Yangtze River and has a climate that is heavily influenced by the East Asian Monsoon. The most prominent feature in annual cycle of precipitation, a gradual springtime rise followed by a sharp drop in the early summer, is associated with the build-up and passage
of the Meiyu frontal zone. Downscaling results for this region are shown in Figure 3.

The predictor used is a combination of specific humidity at 850 mb and zonal winds at both 850 and 300 mb. EDMs and GCMs perform similarly representing the annual cycle of precipitation (top panel), with an average ACSS of 0.604 for EDMs compared with 0.605 for GCMs; both generally fail to fully capture the sharp drop in precipitation associated with the Meiyu passage. In the bottom two panels, notable differences between the 1950-1999 to 2050-2099 changes for GCMs and EDMs are seen; while the GCM-projected changes are relatively modest, with small reductions in fall/winter and modest summertime increases, the EDMs show increases in all months, ranging from 10% in April to as high as 50% in October. Jiangxi Province is already one of the wettest parts of China and precipitation increases of the magnitude suggested by these EDMs, should they come to pass, could have a serious impact on flooding in the region.

To further explore possible future changes in the East Asian Monsoon System, the same EDM (that is, trained on Q850-U300-U850 over the same predictor domain) was used to generate 1950-1999 hindcasts and 2050-2099 forecasts of land surface precipitation over eastern China from the southern coast north to the Mongolian border (110°-120°E, 21°-42°N). In the top row of Figure 4, the zonal mean annual cycles of precipitation over the region from ensemble mean GCM and EDM hindcasts are compared with the observed annual cycle. Here, the EDMs clearly do a better job of replicating both the “shape” and local magnitude of precipitation over the monsoon region although, as noted before, both GCMs and EDMs fail to fully capture the sharp June-July drop in precipitation associated with the northward passage of the Meiyu frontal zone out of Jiangxi. In the bottom row
of Figure 4, projected 1950-1999 to 2050-2099 changes from the 9 most skillful GCMs and EDMs are shown in a similar calendar month versus latitude (Hovmoller) format. The differences between the two sets of projections are striking. GCMs (Figure 4d), on average, project small decreases in the southern part of the domain throughout most of the year, except for JJA, which corresponds with the peak of the GCMs’ “monsoon.” In the northern part of the domain, increases are seen throughout the year, with larger increases in mid-summer (suggesting a strengthened Meiyu) and early spring. By contrast, the EDMs project increases in all parts of the domain in all seasons, with the largest absolute increases (Figure 4e) roughly corresponding to the locations and times of highest peak hindcast precipitation. In the already quite wet southern part of the domain, EDMs project rain rates to increase by as much as 4 mm/day. However, relative to 1950-1999 observations, the EDM-projected changes (Figure 4f) look rather different, with the largest percent changes seen during the winter in both the far southern and far northern parts of the domain, where precipitation increases may reach 50%. That both GCMs and EDMs project increasing precipitation (albeit with somewhat different seasonality) in water-stressed but agriculturally important northern China is a particularly interesting result given the much-discussed drying trend observed in this region.

3.4. Central Europe

The final region over which downscaling was performed is a portion of Central Europe, that was examined by Nicholas and Battisti [2011] because NNR shows a large drop in precipitation over this region around 1990 that does not appear in observations (nor does it correspond to any similarly-timed jumps in precipitation over other regions). Downscal-
ing was performed using a combination of specific humidity and geopotential height at 850 mb (Q850-Z850) as the predictor; results are shown and compared with GCMs in Figure 5. GCMs tend to overestimate precipitation in this region, especially during the summer months (also seen by Nicholas and Battisti [2011] in NNR precipitation), while EDMs tend to overestimate precipitation from late fall through early spring (top panel). Ensemble mean ACSS for EDMs is 0.732 compared with 0.545 the corresponding 18 GCMs. Projections from the 9 most-skillful GCMs show increases in the neighborhood of 10% during fall, winter, and spring, with reductions of a similar magnitude during the summer (bottom two panels); the spread in GCM-projected changes is particularly large for the summer months, indicating a high level of uncertainty during this season. By contrast, EDM-projected changes show increases equal to or exceeding those of the GCMs in all months and with considerably less spread. EDM-projected changes are largest in spring and smallest in summer, although these differences are relatively minor.

4. Discussion
Following on the work of Nicholas and Battisti [2011], this study uses the same empirical/statistical downscaling approach to project changes in precipitation between the late 20th and late 21st centuries. To do this, EDMs are first trained on reanalysis predictor fields and observed precipitation, and then projections are made by applying the EDMs to predictor fields obtained from models participating in CMIP3. For late 21st century projections, we use model runs forced by the IPCC SRES A2 emissions scenario. The EDM-generated precipitation is compared with precipitation obtained directly from the GCMs themselves both in terms of skill and projected changes in the annual cycle.
The empirical models described here offer a plausible alternative to both global and regional climate models for projections of future precipitation under climate change scenarios. In general, these EDMs achieve higher levels of skill in replicating the annual cycle for precipitation during the observational period (1950-1999) than do the GCMs alone (for Jiangxi Province, the EDM skill was slightly but not substantially, lower). For three of the four regions investigated in this study, we found non-trivial differences between GCM projections of late 21st century precipitation and the projections of EDMs “forced” by circulation fields from these same GCMs. In general, the EDMs tend to project smaller decreases and larger increases in precipitation compared to the corresponding GCMs, perhaps because the EDMs are explicitly (and linearly) sensitive to increasing atmospheric moisture content, whereas the impact of greater moisture availability is conditioned by other processes in the GCMs. We note, however, that the ensemble spread in EDM projections is always smaller than for the corresponding GCM projections, indicating that regional precipitation is primarily controlled by large scale circulation and that, across the CMIP3 ensemble, the GCM-simulation circulation fields are quite similar to the observed fields. These results suggest, somewhat surprisingly, that the potential reliability of future projections of regional precipitation may be much greater than currently thought. As such, empirical downscaling efforts similar to the one we have described here should be considered, either alongside or perhaps even in place of dynamical models, in climate impacts studies where precipitation (especially on monthly or seasonal mean timescales) is the primary variable of interest.
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References


WMO (2002), Standardised verification system (SVS) for long-range forecasts (LRF), Tech. rep., World Meteorological Organization, attachment II-9 to the Manual on the GDPS (WMO 485), Vol. I.
Figure 1.  (a) Annual cycle of precipitation from observations (black), 18 AR4 GCMs (thin blue), and EDMs driven by Q850-U850-V850 predictor fields from these 18 GCMs (thin red) over the Southeast US for the period 1950-1999. Projected 1950-1999 to 2050-2099 changes in precipitation for the 9 most skillful GCM and EDM hindcasts are shown (b) in mm/day and (c) as a percentage of the observed monthly mean for the period 1950-1999. Broad colored lines indicate ensemble means. Ensemble mean ACSS is 0.82 for EDMs and 0.73 for GCMs.
Figure 2. As with Figure 1, only for the Upper Colorado River basin using the predictor fields Q700-T700-V700. Ensemble mean ACSS is 0.56 for EDMs and -0.11 for GCMs.
Figure 3. As with Figure 1, only for Jiangxi Province using the predictor fields Q850-U300-U850. Ensemble mean ACSS is 0.61 for EDMs and 0.66 for GCMs.
Figure 4. Annual cycle of zonally-averaged (110°-120°E) precipitation for the East Asian Monsoon region from (a) observations, (b) the 9 most-skillful GCMs, and (c) the 9 most-skillful EDM hindcasts for the period 1950-1999. Projected 1950-1999 to 2050-2099 changes in monsoon precipitation are shown for (d) GCMs and (e) EDM hindcasts in mm/day, and for (f) EDM hindcasts as a percentage of the observed monthly mean.
Figure 5. As with Figure 1, only for Central Europe using the predictor fields Q850-Z850. Ensemble mean ACSS is 0.52 for EDMs and 0.37 for GCMs.
Table 1. Predictor variable sets, predictor domain, and test domain for each of the four downscaling regions. Predictor variables are defined as follows: Q850 and Q700 represent specific humidity at 850 and 700 mb; U850 and U300 represent zonal winds at 850 and 300 mb; V850 and V700 represent meridional winds at 850 and 700 mb; and Z850 is the geopotential height at 850 mb.

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<th>region</th>
<th>predictor variable</th>
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<td>114.0°-118.0°E-25.0°-30.0°N</td>
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Table 2. The amplitude of the inter-model spread $S$ in the annual cycle of precipitation from the CMIP3 models (both raw and statistically downscaled) for the period 1950-1999 and 2050-2099 for each of the four regions discussed in this paper. For reference, the observed annual-average precipitation rate over the region is also noted. All entries are reported in mm/day.

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