A Hybrid Dynamical-Statistical Downscaling Technique, Part I: Development and Validation of the Technique

Daniel B. Walton¹
Department of Atmospheric and Oceanic Sciences,
University of California, Los Angeles

Fengpeng Sun
Department of Atmospheric and Oceanic Sciences,
University of California, Los Angeles

Alex Hall
Department of Atmospheric and Oceanic Sciences,
University of California, Los Angeles

Scott Capps
Department of Atmospheric and Oceanic Sciences
University of California, Los Angeles

¹ Corresponding author address: Daniel B Walton, 7229 Math Sciences Building, 405 Hilgard Ave, Los Angeles, CA 90095
E-mail: waltond@atmos.ucla.edu
Abstract

In Part I of this study, the mid-21st-century surface air temperature increase in the entire CMIP5 ensemble is downscaled to very high resolution (2km) over the Los Angeles region, using a new hybrid dynamical-statistical technique. This technique combines the ability of dynamical downscaling to capture fine-scale dynamics with the computational savings of a statistical model to downscale multiple GCMs. First, dynamical downscaling is applied to five GCMs. Guided by an understanding of the underlying local dynamics, a simple statistical model is built relating the GCM input and the dynamically downscaled output. This statistical model is used to approximate the warming patterns of the remaining GCMs, as if they had been dynamically downscaled. The full 32-member ensemble allows for robust estimates of the most likely warming and uncertainty due to inter-model differences. The warming averaged over the region has an ensemble mean of 2.3 °C, with a 95% confidence interval ranging from 1.0 °C to 3.6 °C. Inland and high elevation areas warm more than coastal areas year-round, and by as much as 60% in the summer months. An assessment of the value added by the hybrid method shows that it outperforms linear interpolation in approximating the dynamical warming patterns. These improvements are attributed to the statistical model’s ability to capture the spatial variations within the region more accurately. Additionally, this hybrid technique incorporates an understanding of the physical mechanisms shaping the region’s warming patterns, enhancing the credibility of the final results.
1. Introduction

To make informed adaptation and mitigation decisions, policymakers and other stakeholders need future climate projections at the regional scale that provide robust information about most likely outcomes and uncertainty estimates (Mearns et al. 2001, Leung et al. 2003, Schiermeier 2010, Kerr 2011). The main tools available for such projections are ensembles of global climate models (GCMs). However, GCMs have grid box scales of 1° to 2.5° (~100 – 200 km), often too coarse to resolve important topographical features and mesoscale processes that govern local climate (Giorgi and Mearns 1991, Leung et al. 2003, Caldwell et al. 2009, Arritt and Rummukainen 2011). The inability of GCMs to provide robust predictions at scales small enough for stakeholder purposes has motivated numerous efforts to regionalize GCM climate change signals through a variety of downscaling methods (e.g. Giorgi et al. 1994, Snyder et al. 2002, Timbal et al. 2003, Hayhoe et al. 2004, Leung et al. 2004, Tebaldi et al. 2005, Duffy et al. 2006, Cabré et al. 2010, Salathé et al. 2010, Pierce et al. 2013). The aim of this study is to develop downscaling techniques to recover the full complement of warming signals in the greater Los Angeles region associated with the multi-model ensemble from the World Climate Research Programme's Fifth Coupled Model Intercomparison Project (CMIP5; Taylor et al. 2012; Table 1).

Regional downscaling attempts have been met with significant criticism (e.g., Schiermeier 2010, Kerr 2011, 2013). One major critique is that the downscaled output is constrained by the limitations of the GCM input. By itself, any single GCM may give a
misleading picture of the true state of knowledge about climate change, including in the
region of interest. Results from downscaling this single GCM will likewise be
misleading. Furthermore, the high resolution and realistic appearance of the downscaled
results may give a false impression of accuracy. This perception of accuracy at the
regional scale is especially problematic if a very small number of GCMs are downscaled,
since the uncertainty is dramatically undersampled. In this case, the downscaled output
may not reflect the most likely climate outcomes in the region, and it certainly does not
provide information about how the uncertainty associated with the GCM ensemble
manifests itself at the regional scale. Typically, previous studies have downscaled only
two global models (e.g., Hayhoe et al. 2004, Duffy et al. 2006, Cayan et al. 2008, Salathé
et al. 2010). This is too small an ensemble to obtain meaningful statistics about the most
likely (ensemble-mean) warming and uncertainty (inter-model spread). Instead,
information from a larger ensemble is preferred (Georgi and Mearns 2002, Kharin and
Zwiers 2002). The CMIP3 and CMIP5 ensembles (Meehl et al. 2007; Taylor et al. 2012),
with a few dozen ensemble members, are usually seen as large enough to compute a
meaningful ensemble-mean and span the climate change uncertainty space.

While downscaling of a large ensemble is desirable to compute most likely
outcomes and fully characterize uncertainty, this can be impractical because of the high
computational cost. Dynamical downscaling, in particular, is an expensive technique, and
most studies that perform it have only applied it to a few global models. For example,
Duffy et al. (2006) downscaled PCM and HadCM2 over the western United States, and
Pierce et al. (2013) downscaled GFDL CM2.1 and NCAR CCSM3 over California. There
are other examples of dynamical downscaling of multiple GCMs, such as the
Coordinated Regional Downscaling Experiment (CORDEX; Giorgi et al. 2009), but these are very large undertakings that require coordination of multiple research groups. Furthermore, they tend to span large geographic areas at lower resolutions (roughly 50 km) than needed for the region of interest here. Areas of intense topography and complex coastlines typically need a model resolution finer than 10–15 km (Mass et al. 2002). The greater Los Angeles region contains minor mountain complexes, such as the Santa Monica Mountains, that have a significant role in shaping local climate gradients. These mountain complexes have spatial scales of just a few kilometers, so even higher resolution, with correspondingly higher computational costs, would be needed here. Thus, for the purposes of this study, dynamical downscaling alone is an impractical answer to the need for multi-model downscaling.

Due to its much lower computational cost, statistical downscaling is almost always used for multi-model downscaling (e.g., Giorgi et al. 2001, Tebaldi et al. 2005, Pierce et al. 2013). Unfortunately, statistical methods may not be able to capture important fine-scale changes in climate shaped by topography and mesoscale dynamics. Dynamical downscaling can capture such effects, provided the regional model resolution is high enough (e.g. Caldwell et al. 2009, Salathé et al. 2010, Arritt and Rummukainen 2011, Pierce et al. 2013). Pierce et al. (2013) found that when a pair of global model was dynamically downscaled, the average difference in the annual warming between the Southern California mountains and coast was twice that of two common statistical downscaling techniques. This suggests that statistical downscaling alone may be insufficient in order to capture sharp gradients in temperature change in our region of interest.
Here we provide a hybrid downscaling technique that allows us to fully sample the GCM ensemble with the physical credibility of dynamical downscaling but without the heavy computational burden of dynamically downscaling every GCM. In this technique, dynamical downscaling is first performed on five GCMs. Then, the results from dynamical downscaling are used to identify the common fine-scale warming patterns and how they relate to the major GCM-scale warming features. Based on these relationships, a simple statistical model is built to mimic the warming patterns produced by the dynamical model. In the statistical model, the common fine-scale patterns are dialed up or down to reflect the regional-scale warming found in the particular GCM being downscaled. While scaling of regional climate change patterns has been around since Mitchell et al. (1990) and Santer et al. (1990), the scaling has primarily been relative to the global-mean warming and only within a single GCM (e.g. Cabré et al. 2010). The statistical model described here is more versatile because (1) it works for any GCM, not just those dynamically downscaled; (2) the downscaled warming is dependent on the GCM’s regional mean warming characteristics, not the global mean warming; and (3) this dependence is allowed multiple degrees of freedom, based on the physical processes at play in this particular region.

The construction of a statistical model that mimics dynamical model behavior forces us to understand the physical mechanisms underpinning the regional patterns of change, adding an additional layer of credibility to the results. This addresses another concern about regional downscaling, namely that it is difficult to determine if the regional climate change patterns are credible even if they appear realistic and visually appealing, because the dynamics underpinning them are unclear, undiagnosed, or unknown.
After the statistical model undergoes a rigorous cross-validation procedure and assessment of value added, it is applied to generate the warming patterns for the remaining GCMs in the CMIP5 ensemble. These statistically generated warming patterns represent our best estimate of what the warming would be if dynamical downscaling had been performed on these remaining GCMs. The efficiency of the hybrid technique allows us to downscale multiple emission scenarios and multiple time periods. In Part I, we downscale 32 GCMs for the mid-century period (2041–2060) under RCP8.5. In Part II, we expand this analysis by downscaling the full ensemble for RCP8.5 end-of-century (2081–2100) and RCP2.6 mid-century and end-of-century.

2. Dynamical Downscaling

a. Model Configuration

Dynamical downscaling was performed using the Advanced Research Weather Research and Forecasting Model version 3.2 (WRF; Skamarock et al. 2008). WRF has been successfully applied to the California region in previous work (e.g. Caldwell 2009, Pierce et al. 2013). For this study, we optimized it for the California region with sensitivity experiments using various parameterizations, paying particular attention to the model’s ability to simulate low cloud in the marine boundary layer off the California coast. The following parameterization choices were made: Kain-Fritsch (new Eta) cumulus scheme (Kain 2004); Yonsei University boundary layer scheme (Hong et al. 2006); Purdue Lin microphysics scheme (Lin et al. 1983); Rapid Radiative Transfer Model longwave radiation (Mlawer et al. 1997); Dudhia shortwave radiation schemes (Dudhia 1989). The Noah land surface model (Chen and Dudhia 2001) was used to simulate land surface
processes including vegetation, soil, snowpack and exchange of energy, momentum and moisture between the land and atmosphere.

The three nested domains for the simulations are shown in Fig. 1. The outermost domain covers the entire state of California and the adjacent ocean at a horizontal resolution of 18 km, the middle domain covers roughly the southern half of the state at a horizontal resolution of 6 km, and the innermost domain encompasses Los Angeles county and surrounding regions at a horizontal resolution of 2 km. In each domain, all variables in grid cells closer than five cells from the lateral boundary in the horizontal were relaxed toward the corresponding values at the lateral boundaries. This procedure ensures smooth transitions from one domain to another. Each domain has 43 sigma-levels in the vertical. To provide a better representation of surface and boundary layer processes, the model’s vertical resolution is enhanced near the surface, with 30 sigma-levels below 3 km.

*b. Baseline Simulation and Validation*

Using this model configuration, we performed a baseline simulation whose purpose is two-fold: (1) to validate the model’s ability to simulate regional climate, and (2) to provide a baseline climate state against which a future climate simulation could be compared, to quantify climate change. This simulation is a dynamical downscaling of the National Centers for Environmental Prediction North America Regional Reanalysis (NARR; Mesinger et al. 2006) over the period September 1981 to August 2001. This dataset has 32-km resolution and provides lateral boundary conditions at the outer boundaries of the outermost domain (Fig. 1). It also provides surface boundary conditions over the ocean (i.e., sea surface temperature) in each of the three domains. The simulation
is designed to reconstruct the regional weather and climate variations that occurred in the
derniermost domain during this time period, at 2-km resolution. The model was
reinitialized each year in August, and run from September to August. Because each year
was initialized separately, the time period could be divided into one-year runs performed
in parallel.

The regional model’s ability to reproduce climate variations during the baseline
period was assessed by comparing the output from the baseline climate simulation to the
available observational measurements from a network of 24 weather stations and buoys.
These quality-controlled, hourly, near-surface meteorological observations were obtained
from the National Climatic Data Center (NCDC; http://www.ncdc.noaa.gov/). The point
measurements are located in a variety of elevations and distances from the coast, and are
numerous enough to provide a sampling of the range of temperatures seen across the
region (Fig. 1). However, both the length and completeness of observational temperature
records vary by location. Most locations have reasonably complete records after 1995, so
validation is performed over the 1995–2001 period.

First, we check the realism of the spatial patterns seen in surface air temperature
climatology. Spatial patterns simulated by the model are highly consistent with
observations, as indicated by high correlations between observed and simulated
temperatures within each season (Fig. 2a). This confirms that for each season, the model
simulates spatial variations in climatological temperature reasonably well. The spatial
pattern is particularly well-represented in summer and winter ($r > 0.9$ in both seasons),
although the model exhibits a slight cold bias in the summer. During the transition
seasons, the model and observed spatial patterns are still in broad agreement, with
correlations greater than 0.7. The model’s ability to simulate temporal variability on monthly timescales and longer is also assessed. At each of the 24 locations, the correlation was computed between the observed and modeled time series of monthly-mean temperature anomalies, after first removing a composite seasonal cycle (Fig. 2b). Temporal variability is very well-simulated by the model, with high correlations at all locations.

Fig. 2 demonstrates that the model gives approximately the right spatial and temporal variations in surface air temperature at specific point locations where trustworthy observational data are available. This gives a high degree of confidence that the model is also producing the correct temperature variations in the rest of the region, where observations are absent. And most importantly for this study, it gives confidence that when it comes to surface air temperature, the model provides a realistic downscaling of the regional pattern implicit in the coarser resolution forcing data set. Thus, the dynamically downscaled climate change patterns presented here are very likely a true reflection of how the atmosphere’s dynamics would distribute the warming across the region if climate change signals seen in the global models occurred in the real world.

c. Future Simulations

With the same model configuration as in the baseline simulation, we performed a second set of dynamical downscaling experiments designed to simulate the regional climate state corresponding to the mid–21st century. We applied the pseudo-global warming method (see Rasmussen et al. 2011 and references therein; also Sato et al. 2007, Kawase et al. 2009) to five global climate models in the CMIP5 ensemble corresponding to this time period and the RCP8.5 emissions scenario (See Table 1). To simulate the future period,
we started by calculating the difference between future and baseline monthly climatologies (2041–2060 minus 1981–2000) for each GCM. These differences are the GCM climate change signals of interest. All model variables are included in the calculation of the climate change signal (i.e., 3-dimensional atmospheric variables such as temperature, relative humidity, zonal and meridional winds, and geopotential height and 2-dimensional surface variables such as temperature, relative humidity, winds and pressure). To produce the boundary conditions for the future period, we perturbed NARR data corresponding to the baseline period (September 1981–August 2001) by adding the change in monthly climatology. The resulting simulation can then be compared directly with the baseline regional simulation to assess the effect of the GCM climate change signals when they are included in the downscaling. Because we downscaled the mean climate change signal in each GCM rather than the raw GCM data, we did not downscale changes in GCM variability. Thus, any future changes in variability in the regional simulations are solely the result of WRF’s dynamical response. In addition to imposing a mean climate change perturbation at the lateral boundaries, CO₂ concentrations were also increased in WRF to match CO₂-equivalent radiative forcing in the RCP8.5 scenario.

We first downscaled CCSM4 for a 20-year period and then performed sensitivity testing to see if it was necessary to downscale such a long period to recover the regional temperature change signal. (Using a shorter period when downscaling the other GCMs conserves scarce computational resources.) Because we perturbed each year in the future period with the same monthly-varying change signal from CCSM4, we expected the warming patterns for each year to be relatively similar. In fact, the warming patterns were nearly identical each year: We could have dynamically downscaled only three years and...
recovered an average warming signal within 0.1 °C of the 20-year value. Therefore, the
remaining four GCMs were only downscaled for three years. For each of these GCMs,
the boundary conditions for the future run were created by adding the mean climate
change signal (2041–2060 minus 1981–2000) from the GCM to the three-year period of

d. Warming Patterns

In this section, we examine monthly-mean warming patterns (future minus baseline)
simulated from dynamical downscaling. Fig. 3 shows these warming patterns averaged
over the five dynamically downscaled GCMs. There are two prominent features that can
be understood through underlying physical processes. First, the warming is greater over
land than ocean. This is true for all months, but the effect is particularly evident in the
late spring, summer, and early fall. Differences between warming over the ocean and land
surfaces have been well-documented in GCMs (Manabe et al. 1991; Cubasch et al., 2001;
Braganza et al., 2003, 2004; Sutton et al. 2007; Lambert and Chiang 2007; Joshi et al.
2008; Dong et al. 2009; Fasullo et al. 2010) and the observational record (Sutton et al.
on the continental scale in both transient and equilibrium climate change experiments due
to greater heat capacity and availability of moisture for evaporative heat loss over the
ocean compared to land (Manabe et al. 1991). Moisture availability is particularly low in
arid and semi-arid regions, including a large swath of western North America adjacent to
the greater Los Angeles region.

Land-sea contrast in the warming is present on large scales in each global model’s
climate change signal, but how is this contrast expressed on the regional scale? Local
topography and the circulation simulated by WRF govern which areas have warming that is more ocean-like or land-like. The land-sea breeze brings marine air and its characteristics to the coastal zone on a daily basis (Hughes et al. 2007) which suppresses warming there, keeping it at or near ocean levels. This suppression is limited to the coastal zone because marine air masses cannot easily penetrate the surrounding mountain complexes. Meanwhile, the inland areas separated from the coast by a mountain complex are not exposed to marine air and have similar warming as interior land areas in the global models.

The second prominent feature is the enhanced warming at high elevations, which can be seen by comparing the warming to the domain topography shown in Fig. 1. During winter and spring months, snow-albedo feedback occurs in mountainous areas, a feature also observed previously in California’s mountainous areas by Kim (2001). In a warmer climate, reductions in snow cover result in an increase in absorbed solar radiation, which are balanced, in part, by increased surface temperatures (Giorgi et al. 1997). Early in the year, snow cover at elevations near the snow line is more sensitive to temperature changes than at higher elevations. The decreased snow cover near the approximate snow line results in rings of enhanced warming in March and April. In May and June, snow cover at all elevations may be sensitive to temperature change, leading to larger warming extending all the way up to the mountain peaks.

3.  **Statistical Downscaling**

We constructed a statistical model to accurately and efficiently approximate the warming patterns that would have been produced had dynamical downscaling been performed on the remaining GCMs. The statistical model scales the dominant spatial pattern (identified
through EOF analysis of the dynamical warming patterns) and the regional mean so they are consistent with the regionally averaged warming over the Los Angeles region as well as the land-sea contrast in the warming.

\[ \text{a. Empirical Orthogonal Function Analysis of Spatial Patterns} \]

Empirical orthogonal function (EOF) analysis was performed on the 60 monthly patterns (five models, each with 12 monthly warming patterns) with their regional means removed (Fig. 4). Although EOF analysis is typically applied to temporal anomalies to identify common modes of variability relative to temporal mean, instead we perform EOF analysis on the spatial anomalies to find how warming at in the region differs from the regional average. The leading EOF explains 74% of the variance. It is referred to as the Coastal-Inland Pattern (CIP) henceforth because of its strong positive loadings inland and negative loadings over the coastal zone and ocean. The second and third EOFs (13%, 5% variance explained) may also represent important physical phenomena, but their roles in shaping the warming patterns are much smaller, and we ignore them for the remainder of this paper.

The CIP arises from local dynamics modulating the basic contrast in climate between the land and ocean. These dynamics are apparent in other basic variables shaping the region’s climate. For example, there is a very strong negative correlation (r = -0.97) between the CIP and the baseline period annual-mean specific humidity (Fig. 5), a climate variable that also exhibits a significant land-sea contrast in this region. This relationship arises because the ocean is by far the most consistent source of water for evaporation in this region. Air masses over the ocean are rapidly and continuously resupplied with water vapor as necessary to maintain high relative humidity levels.
Meanwhile, dry air masses over the desert interior remain cut off from moisture sources. In the coastal zone, land-sea breezes and synoptically driven alternations of the onshore and offshore flow pattern (Conil and Hall 2006) generally lead to intermediate moisture levels. Very similar dynamics mediate the warming distribution, as described in Section 2d, with relatively small warming over the ocean, intermediate warming over the coastal zone, and larger warming inland. Thus the CIP is an expression of local atmospheric circulation patterns endemic to the region. Because the mechanisms that create the CIP are independent of the particular GCMs we have chosen, we are confident that the CIP can be used to downscale other GCMs.

The CIP and the regional mean can be linearly combined to closely approximate the dynamically downscaled warming patterns for each month and for each GCM. When linear regression is used to calculate the combination of the regional mean and the CIP that is closest to the dynamical warming pattern, the resulting approximate warming patterns are within 0.19 °C of their dynamical counterparts, on average. (When we repeated this calculation omitting the contribution of the CIP, the error more than doubled to 0.39 °C, indicating the importance of including spatial variations.) Furthermore, at each point in the domain, we calculated the correlation between the dynamically downscaled warming and the linearly approximated warming. The domain average of these correlations is 0.98. This confirms that we can capture nearly all variations in warming just by combining appropriate scalings of the regional mean and the CIP. Therefore, we use these two factors as the basis for our statistical model, as discussed in the next section.
b. Finding Optimal Sample Locations

In order to statistically downscale each of the remaining GCMs in the CMIP5 ensemble, we need to obtain approximate values of the regional mean and land-sea contrast, which we do by sampling the large-scale warming. To find the optimal sample locations, we examined the five GCMs we have dynamically downscaled and identified the points in the large-scale domain that are best correlated with the dynamically downscaled regional mean and land-sea contrast. Since the GCMs have different resolutions, we first interpolated the GCM monthly warming patterns to a common grid (our outermost WRF grid, with 18 km resolution, Fig. 1). The highest correlations between the large-scale warming and the regional mean are found over the adjacent ocean and along the coast (Fig. 6a). Since these correlations were calculated using the monthly averages from each of the five GCMs, they indicate the degree to which sampling at that location would capture both inter-monthly and inter-model variations in the regional mean. If this exercise could be undertaken for all 32 GCMs in the ensemble, the location of the optimal sampling point might be slightly different, due variations in resolution and grid placement between the GCMs. To build in a tolerance for such ensemble-size effects, we sampled over a region encompassing the highest correlated points, rather than just the best-correlated point. The GCM regional mean, $R_{\text{gMean}(gcm)}$, is calculated as the average over all the points a rectangular region with longitude bounds [120.5° W, 117.5° W] and latitude bounds [32° N, 34.5° N] shown in Fig. 6a (black box).

A similar procedure was used to find the optimal locations to sample the land and the ocean warming for calculation of the GCM land-sea contrast. First, the exact values of the land-sea contrast from the dynamically downscaled warming patterns were
calculated by taking the dot product of the monthly-mean warming patterns with the CIP.

These values were then correlated with the GCM warming interpolated to the common 18-km grid (Fig. 6b). The correlations are highest over the high desert of Southern California and Southern Nevada, northeast of our 2-km domain. The GCM inland warming is calculated as the average warming over the rectangular area with longitude bounds [118° W, 113° W] and latitude bounds [34° N, 37.5° N]. To find the location to sample the ocean warming, we repeated this procedure, but using partial correlations with the effect of inland warming removed (Fig. 6c). These partial correlations identify the optimal ocean sampling location to use in conjunction with our previously selected inland location. The GCM ocean warming is calculated as the warming averaged over a rectangular area with longitude bounds [120.5° W, 117.5° W] and latitude bounds [32° N, 34° N]. The GCM land-sea contrast, $\text{LandSeaContrast}(gcm)$, is calculated as the GCM inland warming minus the GCM ocean warming. If the procedure is reversed, and the optimal ocean location is selected before the optimal inland location, they still end up in nearly identical spots.

c. The Prediction Equation

The statistical model approximates the dynamically downscaled warming as a linear combination of the scaled regional mean warming in the GCM and the product of the GCM’s land-sea contrast with the coastal-inland pattern. The prediction equation for the statistically downscaled warming is

$$dT(gcm, month, i, j) = \alpha + \beta \cdot RgMean(gcm, month) + \gamma \cdot LandSeaContrast(gcm, month)$$
where \( (i, j) \) are coordinates in the 2km grid and \( \alpha, \beta, \) and \( \gamma \) are coefficients determined by linear regression (Fig. 7). The values of these coefficients are \( \alpha = 0.14 \, ^{\circ}\text{C}, \beta = 1.10, \gamma = 1.03. \) Since \( \beta \) is close to one, the dynamically downscaled regional mean warming varies nearly equally with sampled regional mean warming in the GCM. However, it is shifted up by 0.14 \( ^{\circ}\text{C} \), which reflects the fact that the predictor (the warming over the coast and adjacent ocean in the GCMs) must be shifted to a slightly greater value to match the dynamically downscaled regional mean, which encompasses inland areas as well. The dynamically downscaled and GCM-sampled land-sea contrasts are nearly the same, as their ratio is approximately one (\( \gamma = 1.03 \)).

d. Validation of the Statistical Model

Cross-validation was performed to assess how accurately the statistical model replicates the warming patterns produced by the dynamical model. The entire statistical model was rebuilt using only four of the five GCMs, and then used to predict the warming of the remaining GCM. This involved first redoing the EOF analysis to find the CIP. (These alternative patterns are nearly identical no matter which model is left out: The correlation between any two is greater than 0.98. This is additional evidence for the robustness of this pattern in regional warming.) Next, the optimal sampling locations were recalculated. They were similarly located in each case. Finally, linear regression was performed to recalculate the parameters \( \alpha, \beta, \) and \( \gamma \). Once the model was rebuilt, it was applied to the remaining GCM. This procedure was performed five times in all, with each GCM taking a turn being omitted from calibration and used for testing. This cross-validation technique gives us five sets of predicted warming patterns that are compared to their dynamical
counterparts. These warming patterns are also used later to assess value added (Section 3e).

The statistical model consistently reproduces the dynamically downscaled warming pattern for the omitted GCM with a reasonable degree of accuracy (Fig. 8, rightmost columns). The average spatial is correlation between the dynamically and statistically generated annual-mean patterns is 0.95. The average root mean squared error (RMSE) in the annual-mean warming patterns is 0.28 °C over the five models. This error has to be viewed in the context of the variations the statistical model is intended to capture. The range of the five annual means averaged over the whole domain is 2.1 °C, about an order of magnitude larger than the error. This error is small enough that substituting the statistical model output for that of the dynamical model does not significantly affect the mean or spread of the ensemble, two of the most important outcomes of a multi-model climate change study like this one. The statistical model is slightly less accurate at reproducing the monthly warming patterns (average RMSE is 0.39 °C) due to greater variety in the monthly patterns. Still, the error is an order of magnitude smaller than the range of the monthly-mean regional-mean warming (3.5 °C). This gives additional confidence that the statistical model can capture even the monthly warming patterns to a reasonable level of accuracy.

e. Value of Incorporating Dynamical Information

The goal of this study is to provide an ensemble of projections, as if all 32 GCMs had been dynamically downscaled. Due to computational limitations, only five GCMs were dynamically downscaled and the remaining 27 GCMs were statistically downscaled using our statistical model that incorporates the dynamically downscaled output. A reasonable
question is whether incorporating the dynamically downscaled output into the statistical model was helpful or if a simple statistical method would have sufficed. We answered this question by comparing the statistically generated warming patterns—generated via cross-validation—and the GCM warming patterns interpolated to the 2-km resolution grid, to see which method produced closer results to the five dynamically downscaled GCMs. Fig. 8 gives a comparison of warming patterns produced by dynamical downscaling, our statistical downscaling technique, and linear interpolation. A comparison to the warming at the nearest GCM grid point, is also included to give an idea of the result if raw GCM data are used, with no downscaling whatsoever.

The statistically downscaled warming patterns are clearly the most visually similar to the dynamically generated warming patterns. However, it is important to verify this observation using objective measures of model skill. We used two metrics: spatial correlation and RMSE (divided into errors in the regional mean and errors in the spatial pattern), shown in Table 2. The average spatial correlation between the statistically downscaled annual-mean warming patterns and the dynamically downscaled patterns is 0.95, compared to 0.79 and 0.64 for the linear interpolated and raw GCM warming patterns, respectively. This demonstrates that the statistical method is superior to linear interpolation at predicting the spatial variations and sharp gradients in warming. For the monthly average patterns, the statistical model also provides added value over linear interpolation. The value added is somewhat smaller because the statistical model dials up or down only one spatially varying pattern (the CIP), while each month has a slightly different characteristic spatial pattern (Fig. 3).
The second metric is root mean squared error (RMSE). For the annual warming, the statistical model adds value by capturing the spatial variations. The statistical model’s spatial error is 0.14 ºC, which is a substantial improvement over linear interpolation and the raw GCM values of 0.20 ºC and 0.26 ºC, respectively. The statistical model is also an improvement over interpolation of the monthly patterns, though the improvement is somewhat smaller. Again, this is likely due to the simplicity of using a single spatial pattern for all calendar months. We experimented with using different spatial patterns for each month. However, the gains in accuracy were minimal and were accompanied by problems arising from small sample sizes. (We had only five dynamically downscaled warming patterns each month to calibrate each monthly-varying model, rather than the 60 patterns used for the original model.) The statistical model provides no added value in predicting the regional mean warming because the GCM warming averaged over the innermost domain is already a good predictor of the dynamical downscaled regional mean.

The biggest advantage of the statistical model comes when we consider the ensemble-mean annual-mean warming. As we have seen, the statistically downscaled, linearly interpolated, and raw GCM warming patterns all have biases relative to dynamical downscaling. However, when we aggregate the approximate warming patterns into a five-model ensemble, the statistical model’s errors cancel out, while those from the other methods do not (Fig. 9). In fact the statistically downscaled ensemble-mean is nearly an unbiased estimator of the dynamically downscaled ensemble mean. The only bias is a slight one at the highest elevations. In contrast, the other two methods have systematic biases as large as 1 ºC in magnitude. These methods give overly smoothed
land-sea contrasts that fail to resolve the sharp gradients in the warming over the
mountains, along the coastline, and in the western part of the domain. Thus, there are
large swathes of the region where the statistical model is necessary to provide an accurate
characterization of the most likely warming outcome.

We note that the error estimates in Table 2 and the patterns in Figs. 8 and 9 are
based on the statistical model built on only four GCMs and their associated regional
warming patterns. Since each GCM has a unique combination of regional mean and land-
sea contrast (Fig. 10), when one is left out, there is a large region of the parameter space
that goes unrepresented in the calibration of the statistical model. Thus the final statistical
model, calibrated using all five GCMs as described in Section 3c, produces results of
even higher quality. In fact, due to use of linear regression, which ensures that
statistically and dynamically downscaled mean warming match, the biases in the
ensemble-mean annual-mean warming are negligible. The final statistical model is used
to generate the results discussed from Section 4 onward.

4. Ensemble-Mean Warming and Uncertainty

The final statistical model (calibrated using all five GCMs) was applied to all 32 CMIP5
GCMs with output available for the RCP8.5 scenario. The GCMs have widely varying
values of the regional mean and land-sea contrast (Fig. 10). The regional mean values
range from 1.4 to 3.3 °C, and land-sea contrast ranges from 0.3 to 1.3 °C. Notably, these
two parameters are also uncorrelated, so pattern-scaling using only a single degree of
freedom would be misleading here. The dynamically downscaled GCMs (Fig. 10,
highlighted in green) approximately span the range of both parameters, confirming that
The statistical model has been validated in the same parameter range in which it is applied. The annual-mean warming patterns that result from plugging these parameters into the statistical model are shown in Fig. 11. There is considerable variation among these warming patterns, underscoring the importance of considering multiple global models when doing regional downscaling.

The ensemble-mean annual-mean warming pattern, as well as upper and lower bounds of the 95% confidence interval, are shown in Fig. 12. The regional mean warming is 2.3 °C, with a lower bound of 1.0 °C and an upper bound of 3.6 °C. This large inter-model spread indicates that the models disagree considerably on the magnitude of warming, even when using the same scenario. However, the global models share the characteristic of more warming inland than over the ocean. The difference in ensemble-mean warming between coastal and inland areas is especially dramatic in the summertime (Fig. 13). The average August difference between the inland and coastal areas is 0.6 °C, with certain locations showing warming elevated above the coastal values by as much as 1.2 °C (+62%).

The winter and spring warming that would occur in the mountains would likely be somewhat larger if we had done dynamical downscaling for all the global models (compare Figs. 3 and 13), because the statistical model underestimates some warming due to snow-albedo feedback. Based on comparisons between the dynamically and statistically downscaled warming patterns for spring (MAM), the springtime ensemble-mean warming would be as much as 0.5 °C or larger in the San Bernardino and San Gabriel Ranges. This is also consistent with the larger errors in the statistical model seen at the highest elevations in Fig. 9g.
5. Discussion

In this paper, we present a hybrid dynamical-statistical approach to downscale the mid-century warming signal in 32 CMIP5 GCMs. First, we used dynamical downscaling to produce warming patterns associated with five GCMs. Then, to save computational resources, a statistical model was built that scales the characteristic dynamically derived patterns according to the regional warming sampled from the global model. This statistical model was then used to approximate the warming that would result if the remaining global models were dynamically downscaled. The ensemble-mean regional-mean warming was projected to be approximately 2.3 °C, with 95% confidence that the warming is between 1.0 °C and 3.6 °C. Thus, the inter-model differences in the GCM outcomes create significant uncertainty in projections of warming over Southern California.

In this hybrid method, statistical downscaling is employed a unique way. First, while statistical models typically relate large-scale GCM output to observations, ours relates GCM output to dynamically downscaled output. This is because our statistical model is designed to be an approximate dynamical model. As we showed in Section 3d, the differences between the dynamically and statistically downscaled patterns are an order of magnitude smaller than inter-model variations in the warming. This means that our statistical downscaling projections for the ensemble-mean warming and spread are reasonable approximations to the projections that would have resulted from dynamically downsampling all 32 models.

The second difference is that our statistical model was built to directly predict the temperature change, as opposed to predicting the future period temperatures and then
differencing them with baseline temperatures, as is typically done. Normally, the
empirical relationship employed by a statistical model is derived from the historical time
period and then applied to a future time period. This leads to stationarity concerns
because the relationship between predictor and predictand may not hold in the future
period (Wilby and Wigley 1997). In contrast, our statistical model uses a mathematical
relationship between the temperature change in the GCM and the temperature change
produced by dynamically downscaling. Therefore, we have a different stationarity
assumption—one that is easier to satisfy—that the remaining GCMs have values of mid-
century regional-mean warming and land-sea contrast within the range of the five we
dynamically downscaled. Since this condition is satisfied, we have confidence that the
statistical relationships hold for all the GCMs that we downscale.

The statistical model adds value by capturing the fine-scale spatial variations in
the warming. Inland and mountain locations are expected to warm up considerably more
than coastal areas, especially during the summer months. When we compared the
statistically downscaled patterns to the raw and linearly interpolated GCM patterns, the
statistical model captured these spatial variations much more accurately. Furthermore,
when we take an ensemble average of the warming patterns, the errors in the statistically
downscaled patterns nearly cancel out, revealing only minor biases. In contrast, the raw
and linear interpolated GCM warming patterns have large systematic biases, especially
along the coastline and in topographically complex regions that are not resolved well in
the GCMs. The statistical model does not improve upon the GCM estimates of regional
mean warming estimates, because the GCM warming averaged over our innermost
domain is already a good predictor of the dynamically downscaled regional mean.
Another advantage of our hybrid method is that it reflects our understanding of regional climate dynamics. Some types of statistical models, like those based on artificial neural networks, have the effect of being “black boxes,” where the mathematical relationships have no clear physical interpretation. Unlike those techniques, our method first employs dynamical downscaling, which allows us to identify two important physical mechanisms controlling the warming. The first is that the local atmospheric circulation leads to warming over the coastal ocean similar to that seen over the ocean in GCMs, warming over the coastal zone that is slightly elevated above the ocean values, and much higher warming over inland areas separated from the coast by mountain complexes. The second mechanism, smaller in spatial scope, is snow-albedo feedback, which leads to enhanced warming in the mountains. With this knowledge, we built a statistical model that scales the characteristic spatial pattern (which contains signatures of both mechanisms) to fit with the large-scale land-sea contrast and regional mean warming. Because the warming patterns produced by the hybrid approach reflect physical understanding of the region’s climate, they have an extra layer of credibility. Suppose, for instance, that the real climate does warm more over the interior of western North America than over the northeast Pacific Ocean over the coming decades, as is likely if GCM projections are correct. Given the realistic behavior of the WRF model in distributing humidity and temperature across the landscape, it seems very likely that the associated warming pattern in the greater Los Angeles region would be characterized by sharp gradients separating the desert interior and coastal ocean, and that these gradients would be distributed across the landscape in a way very similar to the regional warming patterns we present here.
In Part II of this study, we apply the hybrid technique developed here to other scenarios and time periods. We examine the differences between mid-century (2041–2060) and end-of-century (2081–2100) warming and demonstrate how emission scenario has a much larger effect at end of the century. We also explore how warming effects the diurnal cycle and the number of extreme heat days. In a separate study, Berg et al. (*in preparation*) use a similar hybrid dynamical-statistical approach to downscale the CMIP5 ensemble’s mid-century precipitation projections to the greater Los Angeles region.

**Acknowledgments**

Support for this work was provided by the City of Los Angeles and the US Department of Energy as part of the American Recovery and Reinvestment Act of 2009. Additional funding was provided by the National Science Foundation (Grant #1065864, "Collaborative Research: Do Microenvironments Govern Macroecology?") and the Southwest Climate Science Center. The authors would like to thank Dan Cayan for reviewing an early draft of this work.

**References**


List of Figures

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FIG 5: Coastal-Inland Pattern (left) and surface specific humidity climatology (g kg$^{-1}$) of the baseline period (right). The two spatial patterns are highly correlated ($r = -0.97$).

FIG. 6: Correlations between GCM warming (interpolated to an 18-km grid) and the dynamically downscaled (a) regional mean warming and (b) land-sea contrast in the warming. The sampled regional mean warming and inland warming are calculated as averages over the warming in the black boxes in panels (a) and (b), respectively. Panel (c) shows partial correlations between the interpolated GCM warming and the dynamically downscaled land-sea contrast with the effect of the sampled inland warming removed. The ocean warming is calculated as the average over the black box in (c).

FIG. 7: Scatter plots of dynamically downscaled regional mean warming versus GCM-sampled regional mean warming (left), and dynamically downscaled land-sea contrast versus the GCM-sampled land-sea contrast (right). For each GCM (colors), the twelve monthly-mean warming values are shown. Approximations used by the statistical model are shown as black dashed lines.

FIG.8: Annual-mean warming projections (°C) for five GCMs produced by four different methods: nearest GCM grid box (first column), linear interpolation of GCM (second column), statistical downscaling with the hybrid technique (third column), and dynamical downscaling (fourth column). Projections are for mid-century (2041-2060) relative to the baseline period (1981-2000) under the RCP8.5 scenario. The statistically generated
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FIG. 11: Annual-mean warming patterns (°C) generated by applying the statistical model to all 32 GCMs. Warming patterns are shown for the mid-century period (2041-2060) relative to the baseline period (1981-2000), under the RCP8.5 scenario.

FIG. 12: Ensemble-mean annual-mean warming and upper and lower bounds (°C), based on a 95% confidence interval, for 32 statistically downscaled GCMs run with the RCP8.5 scenario.

FIG. 13: Ensemble-mean monthly-mean warming (°C) computed by averaging the monthly statistically downscaled warming patterns over 32 CMIP5 GCMs.
TABLE 1. Details of the WCRP CMIP5 global climate models used in this study. Check marks indicate which scenarios are used. Five models were dynamically downscaled (bold). All available models are statistically downscaled using the hybrid method.

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TABLE 2. Comparison of the spatial correlation and root mean squared error (RMSE) for
the raw GCM, linear interpolated and the statistically downscaled warming patterns,
relative to the dynamically downscaled warming. By virtue of their orthogonality, errors
in regional mean and spatial pattern are shown separately.

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Note: **Bolded** values indicate improvements over linear interpolation.
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