A Hybrid Dynamical-Statistical Downscaling Technique, Part II: End-of-Century Warming Projections Predict a New Climate State in the Los Angeles Region

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Abstract

Using the hybrid downscaling technique developed in Part I, temperature changes relative
to a baseline period (1981–2000) in the greater Los Angeles region are downscaled for
two future time slices: mid-century (2041–2060) and end-of-century (2081–2100). Two
representative concentration pathways are considered, corresponding to greenhouse gas
emission reductions over coming decades (RCP2.6), and to continued 21st-century
emissions increases (RCP8.5). All available global climate models from the Coupled
Model Intercomparison Project Phase 5 (CMIP5) are downscaled to provide likelihood
and uncertainty estimates. By end-of-century under RCP8.5, a distinctly new regional
climate state emerges: Average temperatures will almost certainly be outside the
interannual variability range seen in the baseline. Except for the highest elevations and a
narrow swath very near the coast, land locations will likely see 60–90 additional
extremely hot days per year, effectively adding a new season of extreme heat. In
mountainous areas, a majority of the many baseline days with freezing nighttime
temperatures will most likely not occur. According to a similarity metric that measures
daily temperature variability and the climate change signal, the RCP8.5 end-of-century
climate will most likely be only about 50% similar to the baseline. For mid-century under
RCP2.6 and RCP8.5, and end-of-century under RCP2.6, these same measures also
indicate a detectable though less significant climatic shift. Therefore, while global
emissions reduction measures would not prevent climate change at this regional scale in
the coming decades, their impact would be dramatic by the end of the 21st century.
1. Introduction

In Part I of this study (referred to hereafter as “Part I”), we described a hybrid dynamical-statistical technique for downscaling the Coupled Model Intercomparison Project Phase 5 (CMIP5) global climate models (GCMs) to 2-km-resolution over the greater Los Angeles region. As an example of its capabilities, we applied this technique to all available CMIP5 GCMs for the RCP8.5 anthropogenic greenhouse gas emissions scenario and projected the mid-century most likely (ensemble-mean) surface air warming and uncertainties arising from multiple GCMs. Part I was a “proof-of-concept” study demonstrating that the hybrid dynamical-statistical technique is capable of accurately capturing both large-scale warming and the spatial gradients in warming within the region due to its complex orography and coastlines. In this study, we use the hybrid dynamical-statistical technique to make a comprehensive assessment of the effects of 21st-century warming in the region, as a function of time period and forcing scenario.

CMIP5 provides a multi-model context for understanding global climate and climate change and also provides a range of multi-century climate responses across GCMs under multiple anthropogenic forcing scenarios (Taylor et al. 2012). The organizers of the CMIP5 archive have adopted a set of forcing scenarios known as Representative Concentration Pathways (RCPs; Moss et al. 2008, Meinshausen et al. 2011, Taylor et al. 2012). Four RCPs have been developed: RCP2.6, RCP4.5, RCP6, and RCP8.5, corresponding to the approximate radiative forcing they would produce at the end of the 21st century (2.6, 4.5, 6.0, and 8.5 watts per square meter [W m⁻²], respectively). The radiative forcing from 1850 to 2100 is shown in Fig. 1a for each scenario, with the historical forcing also shown up to the year 2005. RCP2.6 is
representative of a “mitigation” scenario in which greenhouse gas emissions peak within
the next three decades. The resulting carbon dioxide (CO₂) equivalent concentration,
comprising the net effect of all anthropogenic forcing agents, reaches a maximum
level of approximately 460 parts per million by volume (ppmv) around 2050 and declines
thereafter to approximately 420 ppmv by 2100 (Fig. 1b). Total radiative forcing relative
to pre-industrial levels peaks at about 3 W m⁻² in the middle of the 21st century and
declines to 2.6 W m⁻² by 2100. In contrast to RCP2.6, RCP8.5 represents a “business as
usual” scenario, in which greenhouse gas emissions continue to increase throughout the
21st century. The result is a total radiative forcing of 8.5 W m⁻² and CO₂-equivalent
concentrations greater than 1200 ppmv by 2100. Between the “mitigation” RCP2.6
scenario and the most aggressive “business as usual” RCP8.5 scenario are two
“stabilization” scenarios, RCP4.5 and RCP6. In this study, however, we focus on the
climate response to the two scenarios at either extreme, i.e., RCP8.5 and RCP2.6, to
approximately sample the full range of climate outcomes associated with potential future
emissions.

A sampling of the global-mean surface air temperature response to the RCP2.6
and RCP8.5 scenarios seen in the CMIP5 GCMs is shown in Fig. 1c. (Table 1 of Part I
summarizes the available global climate models used in this study.) For both scenarios,
there are clearly significant model-to-model differences in the warming response over the
21st century. For example, by 2100, for RCP2.6 scenario, surface air warming ranges
from about 0.5 °C to 2.5 °C, while for RCP8.5 scenario, the warming is about 3 °C to 6
°C. The variations in warming arise principally from differences in the GCMs’ spatial
resolutions and physical parameterizations, representing sub-grid processes, e.g., cloud,
the atmospheric boundary layer schemes, etc. Thus the various lines seen in Fig. 1c approximately represent the range of warming outcomes associated with different GCMs. For this reason, we interpret the range of outcomes as the climate change uncertainty associated with a given emissions scenario. We also interpret the average response of all the GCMs for a given emissions scenario (the “ensemble-mean”) as the most likely outcome for that scenario. This assumes the GCMs randomly sample the true uncertainty space associated with the simulated response to anthropogenic forcing. This is the same approach to likelihood and climate change uncertainty quantification used in previous Intergovernmental Panel on Climate Change (IPCC) reports (IPCC 2013).

In this study, we focus on three time periods: “baseline” (1981–2000), “mid-century” (2041–2060), and “end-of-century” (2081–2100). These time periods are shaded in Fig. 1. Climate change is quantified by comparing mid-century and end-of-century climate states to that of the baseline. Previously, the vast majority of regional climate change studies have been performed for only one to three different GCMs (e.g., Hayhoe et al. 2004, Duffy et al. 2006, Déqué et al. 2007, Sato et al. 2007, Cayan et al. 2008, Salathé et al. 2010, Cabré et al. 2010). This is partly due to the computational expense of dynamically downscaling each GCM. The hybrid dynamical-statistical technique described in Part I allows us to perform downscaling of the temperature change signal for each of these future time periods and scenarios, and for every available CMIP5 model. This hybrid dynamical-statistical technique combines the ability of dynamical downscaling to capture fine-scale dynamics with a computationally efficient statistical model to downscale a large ensemble of GCMs. First, the Weather Research and Forecasting (WRF) regional model is used to perform two types of simulations: 1) a
baseline simulation using the North American Regional Reanalysis (NARR) data as boundary and initial conditions; and 2) multiple mid-century future simulations under RCP8.5 emissions scenario by applying a previously established method (e.g., Schär et. al. 1996, Hara et al. 2008, Kawase et al. 2009) to five selected GCMs, which adequately sample the range of warming amplitudes across all GCMs. In this method, initial and boundary conditions are given by adding a mean climate change signal from a given GCM to the 3-hourly NARR 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. We further discuss the caveats of this approach in Section 4. Guided by an understanding of the underlying local dynamics, a simple statistical regression model is constructed relating the GCM input and the dynamically downscaled output. The statistical model consists of mathematical relationships between key aspects of the GCM warming and the warming patterns produced by dynamically downscaling. This statistical model is then used to approximate the warming patterns of the remaining GCMs, as if they had been dynamically downscaled. For more details on this hybrid approach, refer to Part I.

Because we downscale the entire ensemble of GCMs, we can quantify both the ensemble-mean warming and the intermodel spread. This allows us to provide estimates of the most likely outcome and the associated uncertainty.

A robust baseline simulation (validated for surface air temperature in Part I) allows us to evaluate these climate change signals in the context of the region’s substantial natural variability (Wilkinson and Rounds 1998, Abatzoglou et al. 2009). Global-mean temperatures have already increased beyond the envelope of variability
(Bindoff et al. 2013). However, elevated levels of natural variability at the regional scale make this a more difficult test for regional temperatures, depending on location (Deser et al. 2012a, 2012b; Deser et al. 2013; Wallace et al. 2013). This is not just an abstract statistical question. The envelope of natural variability maps out a range of physical states to which the region’s inhabitants and ecosystems are already adapted. Any perturbation due to anthropogenic climate change therefore must be assessed against this background. Here we present multiple analyses designed to reveal whether changes in the region’s temperatures represent significant departures from the baseline state for each scenario and time slice. These include a comparison of the climate change signal to interannual variability and the region’s seasonal cycle, a “similarity” metric that quantifies the degree of correspondence between the daily temperature variability of future climate and the baseline, and quantification of changes in extremely hot and cold days.

Such definitive assessments of most likely outcomes and uncertainty estimates against the background of natural variability allow us to address how choices relating to greenhouse gas emissions affect climate outcomes at the regional scale, and when these outcomes will emerge. This information is a foundation for efforts to adapt to climate change and also reveals the climate benefits of mitigation strategies.

The paper is organized as follows. The surface air warming comparison for multiple time periods and scenarios is shown in Section 2, followed by analyses of these changes relative to the baseline seasonal cycle and interannual variability. Changes in temperature distribution and temperature extremes are assessed in Section 3. In Section 4, we summarize the major findings and discuss the caveats and limitations of this hybrid
dynamical-statistical downscaling approach and the implications for interpreting the downscaled changes.

2. Changes in Mean Temperature

a. Ensemble Mean Change and Spread

First, we examine the annual-mean, ensemble-mean surface air warming (Fig. 2). In each scenario and time slice, the coastal areas warm less than inland areas, with the mountain peaks warming the most. These differences are most pronounced in RCP8.5. As discussed in Part I, spatial variations in the warming are due to (1) generally lower warming over the ocean in response to increasing greenhouse gases, because of the ocean’s relatively larger effective heat capacity and the more efficient ventilation of the ocean surface through latent heat fluxes, which allows enhanced downward infrared radiation in the warmer climate to be balanced with a smaller surface temperature increase over the ocean compared to land; and (2) the land-sea breeze circulation, which introduces a marine influence in the coastal zone, in this case bringing the milder warming of the ocean to the coastal zone. The annual-mean warming is highest in mountain areas mainly because they experience strong snow-albedo feedback, which is strongest in the spring months.

As shown in Fig. 2a, 2b and Fig. 3, the emissions scenario has only a relatively small influence on the warming at mid-century warming. The mid-century warming under RCP2.6 is 70% of the warming under RCP8.5. By the end of century, however, the gap between the scenarios has grown much larger. Under RCP2.6, end-of-century warming remains almost unchanged compared with mid-century warming, whereas under
RCP8.5, end-of-century warming approximately doubles compared with mid-century warming, shown in Fig. 2c, 2d and Fig. 3. This indicates that although the impact of global measures to reduce greenhouse gas emissions would be modest in the coming decades, it would be significant by the time the 21st century draws to a close.

To examine intermodel spread, we look at the annual-mean warming for each GCM, averaged over the land areas within the region (Fig. 3). The intermodel spread scales approximately with the ensemble-mean warming, with the largest spread being associated with end-of-century RCP8.5 (red dots). In this case, the ensemble-mean warming is 4.3 °C, with the model predicting the most warming (MIROC-ESM-CHEM) giving a 6.2 °C increase, and the model predicting the least warming (INM-CM4) giving a 2.8 °C increase. In contrast, under the RCP2.6 scenario, the ensemble-mean warming at end-of-century is 1.6 °C, with a maximum of 2.7 °C and minimum of 0.8 °C. Thus, by the end of the century, even the model with the least warming under RCP8.5 warms more than any model under RCP2.6, despite the large intermodel spread.

b. Comparison of Change Signal to Interannual Variability

To determine if these changes in temperature are outside the variations the region is already adapted to, we compare them to the region’s interannual variability. Fig. 4 shows, for each month of the calendar year, the year-to-year variability in monthly-mean temperatures averaged over land areas in the baseline period, and the associated monthly-mean warming and its intermodel spread for each future scenario and time slice. First, we note that the interannual variability for each month itself varies considerably, with the least variability occurring during the summer months, especially August, and the most variability occurring during the spring and fall months. Thus, the emergence of the
climate change signal from the noise of interannual variability would be a function of
time of year, even if the warming were the same for all months.

Indeed, partly because of low variability in summer, the summer warming signals
are most distinct from the background variability. For example, by mid-century under
RCP8.5, the most likely average future August (predicted by the ensemble-mean) is
warmer than the hottest August during the baseline period. Other months also show most
likely future average temperatures that are outside or near the upper edge of the
variability envelope for this scenario and time slice. By end-of-century under RCP8.5, the
ensemble-mean warming puts average temperatures well outside the baseline range for
every month, even during spring when variability is highest. Again, the effect is most
dramatic in the summer months. For June, July, August, September, and October, even
the model with the least warming predicts average monthly temperatures that are warmer
than the hottest month within the baseline period. For the model with the most warming,
the average future warm-season temperature is about 5 °C greater than the warmest of the
warm months in the baseline period. For the rest of the months, there is little overlap
between the model spread in the average temperatures and the variability envelope. In
fact, December, January, and February will be most similar to average baseline April.
Future March is likely to be warmer than average baseline April; future April is likely to
be warmer than average baseline May. Thus the end-of-century warming signals under
RCP8.5 represent a pronounced shift in climate compared the baseline.

Unlike the end-of-century temperatures under RCP8.5, future temperatures under
RCP2.6 are mostly within the range of baseline variability for both time slices.
3. Changes in Temperature Distribution

In this section we examine changes in daily temperature distribution associated with overall warmer conditions for mid-century and end-of-century time slices under RCP2.6 and RCP8.5 emissions scenarios.

The statistical model presented in Part I was designed only to calculate the change in the monthly climatological mean temperatures for each GCM in the ensemble, and cannot be used directly to calculate changes in temperature distribution. However, changes in daily variability were examined for the five models that were downscaled dynamically. The solid lines of Fig. 5 show probability density functions (PDFs) of baseline and future daily land-averaged temperatures generated through dynamical downscaling for January and July. The shape of future PDF is clearly very similar to that of the baseline for every GCM and for both months. In fact, the future PDF is nearly perfectly approximated by simply shifting the baseline PDF by the mean temperature difference (black dashed lines). This approximation holds equally well for the other 10 months (not shown). We took advantage of this finding to generate future PDFs for all statistically downscaled GCMs, starting with the baseline PDF and then shifting the mean by the temperature change given by the statistical model. To create the ensemble-mean future PDF, we started with the baseline PDF and shifted the mean by the ensemble-mean temperature change. All of the results in this section are based on this technique.

a. Daily-Average Temperature Distributions

Ensemble-mean land-averaged daily temperature distributions are shown for selected months corresponding to the four phases of the annual cycle in Fig. 6 (panels a, b, c, and
d). The most likely warming involves noticeable shifts of the temperature distribution toward higher values. The PDFs themselves are widest in the spring months such as April, and narrowest in summer months such as July. (This is consistent with the smaller levels in interannual variability in summer compared with spring seen in Fig. 4.)

To assess the degree to which daily-average future temperatures will be similar to the baseline, we use a metric that quantifies how similar the current and future temperature distributions are: the fractional of overlap between the two PDFs (example shown in Fig. 6d). The interpretation of this similarity metric is the fraction of days in the future experiencing similar temperatures to the baseline period. The similarity metric is shown in Fig. 6e, for each month and for both time slices and scenarios. In general, it is highest in the spring months, and lowest in the late summer and early fall. This can be traced partly to the differences in variability between these two seasons noted above, and also to the greater warming in late summer/early fall. Both of the time slices associated with the RCP2.6 emissions scenario give similarity scores of about 80%, indicating a pronounced but modest change in climate. The similarity scores for RCP8.5 mid-century are typically about 5 percentage points lower than those associated with the RCP2.6 cases. The RCP8.5 end-of-century case involves a dramatic reduction in the similarity scores, which hover around 45% to 70%. Thus, under RCP8.5, only half to two-thirds of the end-of-century days will experience similar temperatures to the baseline period. This is a strong indicator of a future climate state that is qualitatively different from the baseline.
b. Comparison of Future and Baseline Percentiles

We also provide a complete mapping of the correspondences between baseline and future days. The percentile rank of each day in the baseline is paired with the percentile rank a day with the same temperature would have in a future period. Curves mapping these correspondences between percentiles of daily-averaged temperature in the baseline (x-axis) and future (y-axis) for each time slice and scenario and for each calendar month are presented in Fig. 7. The corresponding percentiles in a future period to the baseline 50th percentile are shown as the vertical lines. The y=x grey lines show what the result would be if there were no changes in the distributions. For example, for July the 50th percentile in the baseline corresponds to the 7th percentile under RCP8.5 at end-of-century (intersection of red curve and vertical gray line). Therefore, 93% of future July days in this time slice and scenario will be warmer than the baseline median temperature. In the case of RCP2.6 at end-of-century, 71% of future July days will be warmer than the baseline median temperature (intersection of magenta curve and vertical gray line), again indicating a noticeable but relatively smaller change in climate. Horizontal lines show the corresponding baseline percentile to the 50th percentile temperature in a given future period under a certain scenario. For example, the 50th percentile for January under RCP8.5 at end-of-century corresponds to the 90th percentile in the baseline; while in the case of RCP2.6 at end-of-century, the 50th percentile for January corresponds to 66th percentile in the baseline. In general, the shape of each curve indicates the similarity of the future state to the baseline, with higher concavity corresponding to a more dramatic shift. The concavity is largest in RCP8.5 at end-of-century, with each percentile in the baseline typically corresponding to a future percentile that ranks tens of percentage points.
lower in the distribution. The concavity is least under RCP2.6, with RCP8.5 at mid-century being somewhat less similar to the baseline than the two RCP2.6 time slices.

c. Heat Extremes

In this study, an extremely hot day is defined as one in which the daily maximum temperature exceeds 35 °C (95 °F). See Appendix for how daily maximum surface air temperature is calculated in this case. Our dynamically downscaled simulation generates temperature snapshots every three hours, and we selected local time 4pm snapshot because it is the closest to the time that the observed maximum temperature typically occurs. The model-calculated daily maximum temperatures from the baseline still validate well against a network of 21 weather stations (Appendix). This gives us confidence that modeled extremely hot days correspond to actual hot days experienced throughout the region.

In the baseline period, most of the coastal and mountain areas have fewer than 10 extremely hot days per year (Fig. 8, top panel). In contrast, inland regions such as the Mojave Desert, Coachella Valley, and Central Valley all contain areas exceeding 100 extremely hot days per year. While frequent extreme temperatures are mostly limited to inland regions, parts of the coastal zone have more than 60 extremely hot days per year. These regions are valleys that are somewhat removed from the moderating effects of the sea breeze, despite lying on the coastal side of the major mountain complexes. Strong gradients in the number of extremely hot days—such as those within in the coastal zone—is an important reason to perform dynamical downscaling to such high resolution. With lower resolution, it could be difficult to distinguish important differences in extreme temperature behavior between these locations.
To quantify future extremely hot days, we started by examining the dynamically downscaled simulations. We found that the distributions of future daily maximum temperatures could be approximated almost perfectly by the baseline distribution shifted by the change in average temperature. (These results are not shown, but they are very similar to the daily-mean results shown in Fig. 5.) Taking advantage of this finding, we created future distributions of daily maximum temperatures by shifting the baseline distributions by the temperature changes provided by the statistical model. These future distributions, generated based on the ensemble-mean warming, were used in the analysis that follows.

The number of extremely hot days increases most under the RCP8.5 scenario. With the exception of the highest elevations and a narrow swath very near the coast, where the increases are confined to a few days, land locations see 60–90 additional extremely hot days per year by end-of-century (Fig. 8, bottom panels). Thus most land areas will effectively experience a new season of extreme heat. Downtown Los Angeles will see a rise from 6 to 54 extremely hot days, while at Lancaster the number will roughly double, from 55 to 119 (Table 1). For mid-century under RCP8.5, and under RCP2.6 for both time slices, the spatial pattern is similar to RCP8.5 end-of-century, but the increases are smaller. Most land areas see increases of roughly 20–40 additional extremely hot days per year. Downtown Los Angeles will experience a dozen or so more extremely hot days, roughly a tripling, while Lancaster will see approximately a 50% increase (Table 1). The highest elevations and locations very near the coast see almost no change in this quantity.
Although areas with more extremely hot days during the baseline period generally also see larger increases, the largest increase actually occurs in the San Gabriel Valley, a part of the coastal zone. This phenomenon can be understood by examining the baseline and future distributions shown in Fig. 9. (Future distributions shown are for RCP8.5 at end-of-century.) At the San Gabriel Valley location where the largest increase in extremely hot days occurs (Fig. 9a), the peak in the baseline maximum temperature distribution occurs at about 32.5 °C. Thus a warming of 4 °C pushes the peak of the distribution well past the 35 °C threshold, resulting in nearly a quadrupling of the number of extremely hot days, from 32 per year in the baseline to 117 at end-of-century. In contrast, at a location in the Mojave Desert farther inland (Fig. 9c), the increase is smaller (from 89 to 142), even though the baseline number of extremely hot days is larger. Despite the fact that the warming is about 0.7 °C (17%) larger here than in coastal zone, the increase in extremely hot days is smaller because the baseline distribution is broader and its peak already lies above the 35 °C threshold. In much cooler coastal locations closer to the ocean, such as Santa Monica (Fig. 9d), few baseline days are close to the threshold, so that a warming of 4 °C only results in an increase from 0 to 3 extremely hot days per year.

The generally greater warming in the interior could be a factor behind the larger increases in the numbers of extremely hot days in these locations. However, the results discussed above suggest that given an approximation of the overall warming in the region, the relationship between the baseline temperature distribution and the 35 °C threshold may be more important in determining the increase in the number of extremely hot days at any particular location. A sensitivity test was performed to see if differences
in warming throughout the domain were, in fact, important factors: The baseline
distribution at each of our selected locations was shifted to reflect the same warming
(Fig. 9, red dashed lines). In this case we chose the warming that occurs at the coast. To
assess the impact of spatial variations in the warming, the resulting number of future
extremely hot days can be compared to the number that takes into account the local
warming (Fig. 9, solid red lines). For the San Gabriel Valley and Mojave Desert locations
(Figs. 9a and c), the increase is nearly identical. A somewhat contrasting situation is seen
in the San Gabriel Mountains (Fig. 9b), where a significant fraction (~50%) of the
increase can be attributed to the enhanced warming occurring in the mountains. These
findings suggest that even in this area of complex topography, there is only a modest
benefit to dynamical downscaling in projecting future changes in extremely hot days.
However, a credible downscaling approach is required to reproduce the baseline climate
accurately.

d. Cold Extremes

For the purposes of this study, we define an extremely cold day as one in which the daily
minimum surface air temperature drops below 0 °C. This particular measure of cold
extremes has significance to the hydrological cycle because surface air temperature
relative to the freezing line is tightly linked to the partitioning between rain and snow
during a precipitation event, the freezing and thawing of the snowpack, and frost
formation. This measure of cold extremes also has ecological significance, since freezing
temperatures can eliminate plant and animal pathogens (e.g., Chakraborty 2013; Raffa et
al. 2013). Note that a blend of the surface skin temperature and 2-meter temperature is
used to calculate the surface air temperature (see Appendix).
In the baseline climate simulation, many parts of the region experience virtually no extremely cold days per year (Fig. 10, top panel). However, extremely cold days occur frequently in the region’s mountainous areas, with some high-elevation locations experiencing as many as 200 days per year. Here we focus on changes in the mountainous areas where freezing temperatures occur. Fig. 10 (bottom panels) shows that in future time slices, large reductions in cold days occur at high-elevations. Under RCP8.5, end-of-century changes are especially dramatic, with some portions of the southern Sierra Nevada Mountains, San Gabriel Mountains, and San Bernardino Mountains seeing a decrease of roughly 50–90 days per year. This represents nearly a full quarter of the year reduction in the number of days below freezing. In most cases, the reduction represents a majority of the baseline number. For example, at Big Bear Lake, the number goes down from 142 to 55 days per year, and at Lake Arrowhead, from 54 to 17 (Table 2). At Victorville and Palmdale, freezing temperatures practically disappear. The total area of the region experiencing at least 1 day per year with freezing temperatures decreases to less than half its value in the baseline. Under RCP2.6 for both time slices and under RCP8.5 mid-century, the reductions in the numbers of days per year are generally smaller, usually limited to 20–30 days (Fig. 10 and Table 2), and the total area of the region experiencing at least 1 day per year with freezing temperatures decreases to roughly 80% of its value in the baseline. Though both emissions scenarios and time slices show fewer extremely cold days overall, in none of these four future cases do extremely cold days disappear completely throughout the region. The future occurrence of weather events involving freezing
temperatures in the greater Los Angeles region therefore cannot be interpreted as an absence of climate change.

4. Discussions and Conclusion

Using a dynamical-statistical technique, we downscale temperature change relative to a baseline period (1981–2000) in the greater Los Angeles region for two future time slices: mid-century (2041–2060) and end-of-century (2081–2100). We focus on two representative concentration pathways, corresponding to greenhouse gas emission reductions over coming decades (RCP2.6), and to continued 21st-century emission increases (RCP8.5). We downscale all available global climate models in the CMIP5 ensemble to provide likelihood and uncertainty estimates.

By end-of-century under RCP8.5, a distinctly new regional climate state emerges against a background of considerable natural variability. This can be seen in more than one measure of change. First, average temperatures will almost certainly be outside the interannual variability range seen in the baseline. This statement is most applicable during the summer and fall, when the average future temperature in the model with the least warming is greater than even the very warmest year of the baseline. Second, the number of extremely hot days, defined as days when the daily maximum temperature exceeds 35 °C, will increase significantly. Except for the highest elevations and a narrow swath very near the coast, land locations will likely see 60–90 additional extremely hot days per year, effectively adding an entirely new season of extreme heat. Third, days when minimum temperatures dip below freezing will decrease. In the baseline, there are typically dozens of days per year in mountainous areas when this occurs, but under
RCP8.5 their number typically decreases by more than half. Finally, according to a similarity metric that quantifies the degree of correspondence between baseline and future distributions of daily temperature variability, the RCP8.5 end-of-century climate will most likely be only about 50% similar to the baseline.

Under RCP2.6 for mid-century and end-of-century time slices, these same measures indicate a climate shift that is less pronounced, but still substantial. Future ensemble-mean average temperatures increase, but lie just within the range of baseline interannual variability for all months except August. Therefore, future average monthly temperatures will likely be as warm as the hottest months in the baseline. Extremely hot days will occur more frequently, with roughly 20–40 additional extremely hot days per year over much of the land areas, thought this is noticeably less than the 60–90 additional hot days experienced at the end-of-century under RCP8.5. Freezing days occur less frequently under RCP2.6 at mid-century and end-of-century, but again the reductions under RCP8.5 end-of-century are twice as large. Similarity scores for the RCP2.6 scenario indicate that future daily temperatures will be roughly 80% similar to those experienced during the baseline period. Adaptation to this level of climate change should be easier because future temperatures are mostly still within the envelope of variability to which human inhabitants and ecosystems are accustomed.

At mid-century, warming under RCP2.6 and RCP8.5 is nearly as large as that under RCP8.5, indicating that global emissions reductions would not prevent climate change in the region in the 1st half of the 21st century. At mid-century, warming under RCP2.6 is still 70% of the warming under RCP8.5. Similarity scores for the two cases are within roughly 5% of one another, and the changes in extremely hot and cold days are
similar. Thus, some climatic changes would occur by mid-century regardless of choices regarding emission reductions. However, the impact of global emissions reductions becomes dramatic as the 21st century draws to a close. As we have detailed, they are necessary to prevent a dramatic shift in the regional climate state.

This downscaling approach used in this study allows us to quantify how the GCM climate change signals are expressed at the regional scale without the GCM future simulation being subject to the very large biases often found in the “historical” simulations of GCMs. A caveat of this work is that we only downscale the effects of a change in mean climate. In the dynamical downscaling experiments at the core of our methodology, we add the mean changes between future and baseline 20-year climatologies for each calendar month to the baseline reanalysis boundary and initial conditions. Therefore, our simulations tell us how the baseline period would have been different if the monthly mean climatologies were altered to reflect the GCM climate change signals. This approach is independently developed and is similar to previously developed procedures in recent regional climate downscaling studies, e.g., Schär et al. (1996), Hara et al. (2008), Knutsen et al. (2008), Kawase et al. (2009), Lauer et al. (2010), Rasmussen et al. (2011), Seo and Xie (2011) and Gutmann et al. (2012). It assumes that the weather and transient signals (e.g., frequency and intensity) applied on the model domain’s boundaries remain structurally the same in the future simulation as in the baseline. Accordingly, we do not incorporate the changes in variability from daily to interannual scales in the boundary forcing (e.g., Knutsen et al., 2008, Rasmussen et al., 2011). Therefore, the potential changes in GCM variability are not downscaled. This
could be a limitation of our downscaling technique, especially when it comes to
projecting changes in extremes.

One way to shed light on this issue is to investigate variability changes in the raw
GCM output. We examine the daily PDF distributions within each calendar month for the
five dynamically downscaled GCM projections, for the baseline period and the mid-
century period under RCP8.5 emissions scenario. Fig. 11 compares the distribution of
daily area-mean (117°W–120°W, 33°N–36°N) surface air temperature in January and
July in the two periods. The solid lines show the distribution of baseline (black) and mid-
century (red) separately. While the shapes of the distributions are not identical between
baseline and mid-century for each GCM, they are very similar for both months.

Therefore, the mid-century distribution for each month can be approximated by shifting
the baseline distribution by the mean temperature change (red dashed lines). Examination
of PDFs for the other calendar months reveals that this approximation still holds well (not
shown). These results suggest that in the domain of interest, i.e., the Los Angeles region,
the GCM-derived changes in daily temperature variability are rather small and secondary
to the shift of the mean. It seems unlikely the weather activities would substantially
change in GCMs from the baseline to future in the domain of interest. If these changes in
GCM temperature variability were downscaled, it is likely that they would be equally
subtle in the downscaled data. Therefore, we conclude the local changes in extremely hot
and cold days projected in this study are reasonably accurate and are not subject to the
limitation of the methodology.
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 #EF-1065863, "Collaborative Research: Do Microenvironments Govern Macroecology?") and the Southwest Climate Science Center. The authors would like to thank Dr. Dan Cayan for reviewing an early draft of this work and the two anonymous reviewers for their valuable comments.
APPENDIX

Improving Model Estimates of Extremes

When we used the dynamically downscaled 2-meter air temperature output from the Weather Research and Forecasting (WRF) regional model, the number of simulated extremely hot days (daily maximum temperature, $T_{\text{max}} > 35^\circ\text{C}$) during the baseline period was too low in comparison with observational point measurements (Table A1). In this Appendix we explain the potential causes of the underestimation and then come up with a new formula that better quantifies number of the extremely hot days. This new formula also improves estimates for extremely cold days.

The observational data set used is a set of quality-controlled, daily maximum near-surface temperature observations taken during the baseline period (1981-2000) from 21 weather stations. These data were obtained from the National Climatic Data Center (NCDC; http://www.ncdc.noaa.gov/oa/ncdc/html). Unlike this observational data set, where the temperatures were recorded every 10 min, in our simulations, we only saved a snapshot of the air temperature output every 3 hours (at local times 10am, 1pm, 4pm, 7pm etc.) Since the temperature is not recorded at the exact time the true daily maximum (minimum) is achieved, our modeled maximum (minimum) temperatures will be an underestimation (overestimation) of what WRF actually produced. This leads to an underestimation (overestimation) of the number of extremely hot (cold) days.

Another source of discrepancy may come from the height at which the temperature measurements are taken. To measure surface air temperature in WRF, we use the air temperature at a reference height of 2 meter. While WRF interpolates the temperature to two meters height from the temperature of its atmospheric layer closest to
the surface, the thermometer at the weather stations is set between 1 to 2 meters above the ground. Because the ground is the source of heat during the day, the closer the thermometer is to the ground, the warmer the observed temperature. Therefore the mismatch between the modeled reference height and true observed height may partially account for the model’s bias of the observed surface air temperature. The particular technique used by WRF to interpolate 2-meter temperatures from the temperature of the surface layer may also lead to a bias compared with the observed surface air temperature.

To better diagnose the simulated extremes in the baseline simulation and the future changes, we developed a formula to describe the daily maximum surface air temperature more realistically. We tested a series of different combinations of model simulated surface skin temperature (TSK) and 2-meter air temperature ($T_{2m}$) and found that a combination of two-thirds TSK and one-third $T_{2m}$ gives the most realistic estimation (smallest root-mean-square error) of the observed extremes (Fig. A1). The daily maximum surface air temperature is taken to be this blend of surface and surface air temperatures, taken at 4pm local time. This new method validates well against the point measurements in the observational network and provides a significant improvement over using $T_{2m}$ alone (Table A1). For example, for the city of Lancaster, the new method produces 53 extremely hot days per year, while the observed number of extremely hot days is 56±8 days per year, a significant improvement over the 14 days per year predicted by $T_{2m}$ alone. Because of these improvements, this method is used for the calculations of extremely hot days.

The particular blend of two-thirds surface skin temperature plus one-third 2-meter temperature was also found to produce the best results for modeling daily minimum
surface air temperatures (not shown). As with the maximum temperature, the minimum
temperature can occur at any time. The closest time to the average observed minimum
that a WRF snapshot is taken is 4am local time. Thus daily minimum temperatures are
calculated as a weighted average of 2-meter and surface skin temperatures at 4am local
time.
References


### List of Tables

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<tr>
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TABLE 2: Average number of extremely cold days (daily $T_{\text{min}} < 0^\circ$C) per year for selected sites in the Los Angeles region. Results are shown for the baseline, mid-century and end-of-century projections for both RCP8.5 and RCP2.6 emission scenarios.

<table>
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TABLE A1: Average number of extremely hot days per year for 21 sites in the Greater Los Angeles Area. An extremely hot day is defined as a day in which the daily maximum surface air temperature is greater than 35°C (95°F). Results are shown for station observations, modeled 2-meter air temperature ($T_{2m}$), and weighted average of modeled $T_{2m}$ and surface skin temperature (TSK).

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FIG. 1: (a) Total radiative forcing (anthropogenic plus natural) and (b) Carbon dioxide (CO₂) equivalent concentrations for approximately the past century and four Representative Concentration Pathways: RCP8.5, RCP6, RCP4.5, and RCP2.6 (also called RCP3-PD); (c) Global-mean surface air temperature departures from 1981–2000 mean as simulated in all CMIP5 GCMs used in this study for the historical forcing (black), and RCP8.5 (red) and RCP2.6 (blue). Gray shaded regions denote the baseline (1981–2000), mid-century (2041–2060), and end-of-century (2081–2100) periods used in this study.

FIG. 2: Ensemble-mean of statistically downscaled annual-mean surface warming (°C) for (a) mid-century (2041–2060) under RCP2.6; (b) mid-century under RCP8.5; (c) end-of-century (2081–2100) under RCP2.6; and (d) end-of-century under RCP8.5. White contours are plotted at 1000m elevation.

FIG. 3: Land-averaged annual-mean surface warming (°C) statistically downscaled from each GCM for mid-century (2041–2060) under RCP2.6 (green dots); mid-century under RCP8.5 (orange dots); end-of-century (2081–2100) under RCP2.6 (magenta dots); and end-of-century under RCP8.5 (red dots). Horizontal lines denote the corresponding ensemble-mean across all GCMs.

FIG. 4: Annual cycle of land-averaged surface air temperature (°C) for the baseline period (black), mid-century under RCP2.6 (green), mid-century under RCP8.5 (orange),
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FIG. 5: Probability density functions (PDFs) of daily-mean land-averaged surface air temperature during January and July, during the baseline period (black) and at mid-century under RCP8.5 (orange) for 5 dynamically downscaled GCMs. The baseline distribution shifted by the statistically downscaled mean temperature change (dashed black) is shown for comparison.

FIG. 6: (a-d) Probability density functions (PDFs) of ensemble-mean daily-mean land-averaged surface air temperature (°C) during January, April, July and October, representing each season in the baseline period (black) and at mid-century under RCP2.6 (green), mid-century under RCP8.5 (orange), end-of-century under RCP2.6 (magenta), and end-of-century under RCP8.5 (red); (e) Similarity score for each future scenario and time slice, defined as the percentage of area overlapping between future PDF and baseline PDF.

FIG. 7: Correspondence between percentiles of daily-averaged temperature in the baseline (x axis) and future period (y axis) for each calendar month and for mid-century and end-of-century for RCP8.5 and RCP2.6 scenarios. The corresponding percentile in
the future (baseline) to the baseline (future) 50th percentile is shown as the vertical (horizontal) gray line.

FIG. 8: The number of extremely hot days per year (daily maximum surface air temperature, \( T_{\text{max}} > 35^\circ\text{C} \)) for the (a) baseline; and the change of number of extremely hot days per year for the (b) mid-century under RCP2.6; (c) mid-century under RCP8.5; (d) end-of-century under RCP2.6; and (e) end-of-century under RCP8.5. The 1000m elevation contour is shown in white.

FIG. 9: PDFs of daily maximum temperature at selected sites during warm months (June to October) for baseline period (solid black); end-of-century under RCP8.5 (solid red); baseline shifted by warming at Santa Monica location (dashed red). Vertical line indicates 35°C threshold.

FIG.10: The number of extremely cold days per year (daily minimum surface air temperature, \( T_{\text{min}} < 0^\circ\text{C} \)) for the (a) baseline; and the change of number of extremely cold days per year for the (b) mid-century under RCP2.6; (c) mid-century under RCP8.5; (d) end-of-century under RCP2.6; and (e) end-of-century under RCP8.5. The 1000m elevation contour is shown in white.

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