2-2013

Probabilistic estimates of future changes in California temperature and precipitation using statistical and dynamical downscaling

David W. Pierce

Tapash Das

Daniel R. Cayan

Edwin P. Maurer

Santa Clara University, emaurer@scu.edu

Norman L. Miller

See next page for additional authors

Follow this and additional works at: <https://scholarcommons.scu.edu/ceng>

Part of the [Civil and Environmental Engineering Commons](#)

Recommended Citation

Pierce, D.W. T. Das, D.R. Cayan, E.P. Maurer, N. Miller, Y. Bao, M. Kanamitsu, K. Yoshimura, M.A. Snyder, L.C. Sloan, G. Franco, M. Tyree, 2013, Probabilistic estimates of future changes in California temperature and precipitation using statistical and dynamical downscaling, *Climate Dynamics* 40(3-4):839-856, DOI: 10.1007/s00382-012-1337-9.

The final publication is available at Springer via <http://doi.org/10.1007/s00382-012-1337-9>.

This Article is brought to you for free and open access by the School of Engineering at Scholar Commons. It has been accepted for inclusion in Civil Engineering by an authorized administrator of Scholar Commons. For more information, please contact rsroggin@scu.edu.

Authors

David W. Pierce, Tapash Das, Daniel R. Cayan, Edwin P. Maurer, Norman L. Miller, Yan Bao, M. Kanamitsu, Kei Yoshimura, Mark A. Snyder, Lisa C. Sloan, Guido Franco, and Mary Tyree

1 **Probabilistic estimates of future changes in**
2 **California temperature and precipitation using**
3 **statistical and dynamical downscaling**

4 David W. Pierce^{1,*}

5 Tapash Das^{1,6}

6 Daniel R. Cayan¹

7 Edwin P. Maurer²

8 Norman L Miller³

9 Yan Bao³

10 M. Kanamitsu¹

11 Kei Yoshimura¹

12 Mark A. Snyder⁴

13 Lisa C. Sloan⁴

14 Guido Franco⁵

15 Mary Tyree¹

16 ¹*Scripps Institution of Oceanography, La Jolla, CA*

17 ²*Santa Clara University, Santa Clara, CA*

18 ³*University of California, Berkeley, Berkeley, CA*

19 ⁴*University of California, Santa Cruz, Santa Cruz, CA*

20 ⁵*California Energy Commission, Sacramento, CA*

21 ⁶*CH2M HILL, Inc., San Diego, CA*

22 *Corresponding Author address: SIO/CASPO, Mail stop 0224, La Jolla, CA,
23 92093-0224. dpierce@ucsd.edu, 858-534-8276. Fax: 858-534-8561

24 Version 2 27 February 2012

25 **ABSTRACT**

26 Sixteen global general circulation models were used to develop probabilistic projections of
27 temperature (T) and precipitation (P) changes over California by the 2060s. The global models
28 were downscaled with two statistical techniques and three nested dynamical regional climate
29 models, although not all global models were downscaled with all techniques. Both monthly and
30 daily timescale changes in T and P are addressed, the latter being important for a range of
31 applications in energy use, water management, and agriculture. The T changes tend to agree more
32 across downscaling techniques than the P changes. Year-to-year natural internal climate variability
33 is roughly of similar magnitude to the projected T changes. In the monthly average, July
34 temperatures shift enough that that the hottest July found in any simulation over the historical
35 period becomes a modestly cool July in the future period. Januarys as cold as any found in the
36 historical period are still found in the 2060s, but the median and maximum monthly average
37 temperatures increase notably. Annual and seasonal P changes are small compared to interannual
38 or intermodel variability. However, the annual change is composed of seasonally varying changes
39 that are themselves much larger, but tend to cancel in the annual mean. Winters show modestly
40 wetter conditions in the North of the state, while spring and autumn show less precipitation. The
41 dynamical downscaling techniques project increasing precipitation in the Southeastern part of the
42 state, which is influenced by the North American monsoon, a feature that is not captured by the
43 statistical downscaling.

44 **1. Introduction**

45 California has a confluence of factors that make it particularly vulnerable to
46 anthropogenically-induced climate change (e.g., Hayhoe et al. 2004, Cayan et al.
47 2006). Warming and precipitation changes will directly impact crops and pests in
48 the agricultural and wine-producing regions, and affect regional water resources
49 and flood risk through changes in the snow line, snowpack, and
50 evapotranspiration. Indeed, anthropogenic effects can already be seen in the
51 temperature and hydrology of the western U.S. (Barnett et al. 2008, Pierce et al.
52 2008, Bonfils et al. 2008, Hidalgo et al. 2009, Das et al. 2009; cf. Maurer et al.
53 2007, who examined a smaller region).

54 The primary purpose of this work is to present projections of temperature (T) and
55 precipitation (P) change over California by the 2060s in a probabilistic framework
56 (e.g. Manning et al. 2009; Chen et al. 2011), which facilitates risk-based planning
57 and provides a framework for adaptive resource management (e.g., Anderson et
58 al. 2008, Brekke et al. 2009). Global climate models (GCMs; Meehl et al. 2007)
59 do not uniformly sample model uncertainties, and are not independent (Pennell
60 and Reichler, 2011). Therefore the distributions shown here are not true estimates
61 of the probability of future climate changes, rather are best-guess estimates of
62 future climate change given current simulations. We compare our projections of T
63 and P changes to natural internal climate variability, so that the relative magnitude
64 of the two can be assessed.

65 Spatial downscaling is necessary in California, which is topographically complex.
66 We use daily results from two GCMs dynamically downscaled with three different
67 regional climate models; the same two global models plus two more statistically
68 downscaled on a daily timescale; and the same 4 models plus 12 more (some with
69 multiple ensemble members) statistically downscaled by a different technique on a
70 monthly timescale. In total, we incorporate data from 45 runs originally generated
71 by 16 different global models. The secondary purpose of this work is to compare
72 the climate projections from the dynamical and statistical downscaling techniques
73 and address how they systematically differ. Natural internal climate variability is

74 included to the extent that the original GCMs simulate it (cf. AchutaRao and
75 Sperber, 2006).

76 Climate change over California has been extensively studied using some
77 combination of single or multiple GCMs and statistical or dynamical downscaling
78 (e.g., Dickinson et al. 1989; Giorgi et al. 1994; Pan et al. 2001; Kim 2001 and
79 2005; Snyder et al. 2002; Hayhoe et al., 2004; Leung et al. 2004; Brekke et al.
80 2004; Maurer and Duffy 2005; Snyder and Sloan 2005; Duffy et al. 2006; Maurer
81 2007; Liang et al. 2008; Caldwell et al. 2009; Chin et al. 2010). Some common
82 themes emerge from these efforts. First, different GCMs produce different
83 warming and precipitation changes. Second, regional climate models (RCMs)
84 introduce another source of variation, even with the same driving GCM. Third,
85 temperature changes over California are consistently positive, but precipitation
86 changes vary in sign. Fourth, even with the divergent precipitation projections, the
87 effect on California's hydrology is substantial; snowpack declines and runoff
88 shifts to earlier in the water year, with elevation-dependent effects due to the
89 colder temperatures at higher elevations. And fifth, all model simulations exhibit
90 biases, which are assumed to systematically affect the projected climate as well.

91 Given this body of previous work, it is perhaps surprising that major gaps remain.
92 Few of the studies approached the problem probabilistically, and only Leung et al.
93 2004, Hayhoe et al. 2004, and Kim 2005 analyze the future daily data, which is
94 critical to energy use, agriculture, ecology, flooding, and water management.
95 Finally, none of the studies used both statistical and dynamical downscaling and
96 compared the two (cf. Hay and Clark 2003, who used both, but over the historical
97 period only and examined runoff rather than T and P). Similar issues have been
98 addressed in other regions; for example, Europe in the PRUDENCE (Christensen
99 et al., 2007) and ENSEMBLES (Kjellstrom and Giorgi, 2010) projects, and the
100 UK with the Climate Projections project
101 (<http://ukclimateprojections.defra.gov.uk/>).

102 Pierce et al. (2009) examined 40-year periods over the western U.S., and found
103 that 14 runs developed from 5 global models reliably conveyed the information
104 from the full set of 21 CMIP-3 model results. The bulk of results shown here are
105 generated using monthly data from all 45 runs (developed from 16 global models),

106 so should be reliable even though the spatial and time scales considered here are
107 somewhat smaller than used in Pierce et al. (2009) (California vs. the western
108 U.S., 10-yr vs. 40-yr periods) and natural internal variability becomes more
109 evident at smaller scales (e.g., Hawkins and Sutton 2010). However the analysis
110 shown here was also done with a subset of 25 runs (excluding multiple ensemble
111 members for any single model) and the results were little different, which suggests
112 that our sampling of available climate model ensemble members is adequate.

113 Some of our results are from the 9 daily runs developed from 4 global models,
114 which falls short of the ideal number of runs and global models to use. However
115 Pierce et al. (2009) demonstrates that the large majority of the increase in multi-
116 model ensemble averaged skill occurs when going from 1 to 4 global models. We
117 therefore believe that the daily results shown here, obtained from the 9 runs
118 (incorporating information from 4 global models), are both a credible first analysis
119 of the problem and a roadmap showing how the multi-model probabilistic
120 treatment could be extended with additional runs in the future.

121 **2. Data and Methods**

122 We used dynamical downscaling with 3 regional climate models (RCMs): the
123 Regional Climate Model version 3 (RegCM3), which is derived from NCAR's
124 MM5 mesoscale model (Pal et al. 2007); the NCAR/NCEP/FSL Weather
125 Research and Forecasting (WRF) model (Skamarock et al., 2008); and the
126 Regional Spectral Model (RSM, Kanamitsu et al., 2005), which is a regional
127 version of the National Centers for Environmental Prediction (NCEP) global
128 spectral model. Details of the RCMs are given in the Supplemental Material,
129 section 1. Miller et al. (2009) examined the ability of the RCMs used here to
130 simulate California's historical climate when driven with boundary conditions
131 from the NCEP reanalysis II (Kanamitsu et al. 2002), and compared their
132 climatology to observations. That work concluded that all the models have
133 limitations, particularly in parameterized process such as cloud formation, but that
134 "they perform as well as other state-of-the-art downscaling systems, and all do a
135 credible job simulating the historical climate of California" (see also the
136 supplementary information).

137 We used two methods of statistical downscaling: Bias Correction with
138 Constructed Analogues (BCCA; Hidalgo et al., 2008; Maurer et al. 2010), and
139 Bias Correction with Spatial Disaggregation (BCSD; Wood et al. 2002, 2004)
140 These methods were compared in Maurer and Hidalgo (2008), who concluded that
141 they have comparable skill when downscaling monthly fields of temperature and
142 precipitation. However only BCCA preserves the daily sequence of original global
143 model variability, which is of interest here. Details of the statistical techniques are
144 given in the Supplemental Material, section 2. Some of the BCSD ensemble
145 members were downloaded from the Bias Corrected and Downscaled WCRP
146 CMIP3 Climate Projections archive at [http://gdo-](http://gdo-dcp.ucllnl.org/downscaled_cmip3_projections)
147 [dcp.ucllnl.org/downscaled_cmip3_projections](http://gdo-dcp.ucllnl.org/downscaled_cmip3_projections) (Maurer et al., 2007).

148 All downscaling is to an approximately a $1/8^{\circ} \times 1/8^{\circ}$ (~ 12 km) spatial resolution.
149 Table 1 lists the various models and number of ensemble members used for each
150 downscaling technique. Not all GCMs were downscaled with all techniques,
151 because of the computer time required and lack of daily data for all the GCMs.
152 Only limited time periods were covered: 1985-94 (the “historical period”) and
153 2060-2069 (the “future period”). Also, only the SRES A2 emissions scenario is
154 used. We note that the 2060s is about the last decade where globally averaged
155 surface temperatures from the A2, B1, and A1B emissions scenarios do not show
156 a clear separation (IPCC 2007). For the dynamical and BCCA downscaling,
157 CMIP-3 ensemble number 1 was used when more than one ensemble member was
158 available.

159 The 10-year spans are too short to examine natural climate variability from El
160 Nino/Southern Oscillation (ENSO) and the Pacific Decadal Oscillation (PDO) in
161 any one model run. However, we partially make up for this by using 4 to 16
162 models at a time (depending on the downscaling technique). Natural internal
163 climate variability due to ENSO and the PDO is not synchronized across model
164 runs due to the chaotic nature of the atmosphere. So, for example, one model run
165 might be simulating positive ENSO conditions in model year 2065 while another
166 model run might be simulating negative ENSO conditions. Although both ENSO
167 and the PDO affect California temperature and precipitation, averaging across
168 unsynchronized runs randomly samples different phases of these phenomena,
169 which reduces the net effect of they have on our estimates of anthropogenic

170 climate change by the 2060's. We do not discard these estimates of natural
171 variability; rather we compare our estimates of anthropogenic climate change to
172 the magnitude of this natural variability so that a better understanding of the
173 relative magnitude of each can be obtained.

174 Results are presented as averages over the 11 California climate regions identified
175 by Abatzoglou et al. (2009). These regions do a better job representing
176 California's diverse mix of climate regimes than the standard U.S. climate
177 divisions.

178 **2.1 Bias correction**

179 All T and P fields, whether downscaled statistically or dynamically, underwent a
180 bias correction procedure (Panofsky and Brier 1968; Maurer et al. 2002; Wood et
181 al. 2002, 2004; Maurer 2007; Maurer et al. 2010). This is necessary because the
182 project's focus was on hydrological and other applications, and even current state-
183 of-the-art GCMs/RCMs generate T and P fields with biases, often due to biases in
184 the original global fields (e.g., Wood et al. 2004, Duffy et al. 2006, Liang et al.
185 2008). Details of the bias correction procedure are given in the Supplemental
186 Material, section 3.

187 **3. Results**

188 The probabilistic framework requires that several model runs be included to
189 provide a distribution of projected outcomes. In this work we weight all
190 combinations of global model and downscaling technique equally (except for the
191 multiple ensemble members available from a single global model using BCSD, as
192 described below), following the approach used in the last IPCC assessment (IPCC,
193 2007). Pierce et al. (2009) looked specifically at the western U.S. and concluded
194 that weighting by model quality does not make a difference to climate projections
195 until after the time period considered here (the 2060s).

196 BCSD was the only downscaling technique that had multiple downscaled
197 ensemble members available from the same global model (Table 1). When
198 analyzing mean quantities, we combined multiple BCSD downscaled results from

199 the same global model into a single model mean before analysis, so that each
200 global model contributes equally to the BCSD result despite the disparate number
201 of ensemble members. When computing variability measures this averaging is not
202 appropriate, since averaging reduces the range of variability. In these cases we
203 used a Monte-Carlo approach, constructing 1000 random sets of BCSD results
204 where each model contributed one randomly picked ensemble member. Results
205 shown here are the average obtained across the 1000 random trials. In practice
206 however this makes little difference, as the BCSD results are well sampled even
207 excluding the extra ensemble members.

208 **3.1 Temperature changes**

209 Figure 1 (upper) shows the temperature changes by the 2060s, averaged across all
210 models and downscaling techniques. The yearly-averaged warming is on the order
211 of 2.4 C. The coastal regions experience less warming due to the ocean's
212 moderating influence, with a typical value of about 1.9 C. Inland locations show
213 warming approaching 2.6 C, which may have the potential to suppress coastal
214 warming further via enhanced sea breezes in some locations (Snyder et al. 2003;
215 Lebassi et al. 2009). The lower panels of Fig. 1 show climatological fields for
216 reference.

217 The mean warming has a pronounced seasonal signature, with the most warming
218 (~3 C) in the summer (June-July-August), and the least warming (< 2 C) in the
219 winter (Dec-Jan-Feb). Since energy use in California is dominated by summer
220 cooling loads rather than winter heating loads, this warming pattern suggests that
221 peak energy use could increase faster than would be expected if only the yearly
222 averaged temperature changes were taken into account.

223 Figure 2 shows the change in individual monthly distributions of temperature,
224 displayed as a mapping between historic and future percentiles. For example, the
225 blue cross in panel a for the Sacramento/Central valley shows that the 50th
226 percentile temperature in the historical period (x axis) will become the 17th
227 percentile value in the 2060s (y axis). The curves in Fig. 2a start at the origin,
228 which means that the coldest January monthly average temperatures in the
229 historical period will still be experienced in the 2060s. Relative to the evolving

230 mean, the coldest months become much more dramatic in the future, which might
231 have implications for moving to crops better adapted to hotter conditions. Of the
232 45 runs (Table 1), 16 have at least one January in the 2060s that is about as cold,
233 or colder, than the coldest historical January in the same model. Despite this, Fig.
234 2a shows that the median monthly January temperature in the future will be
235 warmer than 8 or 9 out of 10 Januarys today, and the warmest Januarys in the
236 future are completely off the historical distribution.

237 In July (Fig. 2b), the curves still start nearly at the origin, but inspection showed
238 that such a cold July only existed in two of the 45 runs. On the other hand, the
239 difference in the warmest months is profound. Over most of the state, the warmest
240 monthly average July found in the entire historical distribution of any model is
241 only a 15-40th percentile event in the future period. I.e., a July that is record-
242 breaking hot by current historical standards will become modestly cool in
243 comparison to the new mean.

244 The yearly warming simulated by the various downscaling techniques is shown in
245 Fig. 3. Results are illustrated for the GFDL 2.1 and CCSM3 global models. Global
246 model results are displayed in Fig. 3f and 3k for comparison. The downscaling
247 techniques generate similar values, and capture the decrease in warming near the
248 coast that is poorly resolved in the global field. BCCA produces a somewhat
249 weaker trend than the other methods for GFDL, although not for CCSM3 (cf.
250 Maurer and Hidalgo (2008), their Fig. 5).

251 *3.1.1 Distributions of seasonal temperature change*

252 The exceedence probability of each year's seasonally averaged temperature
253 change in the future period is shown in Fig. 4. The data in this figure have been
254 re-sampled using the method described in Dettinger (2005), which fleshes out the
255 distributions using a principal component analysis-based resampling technique
256 applied to the variability around the model-mean climate change signal.

257 Figure 4 shows a distribution composed of one value per year (2060-69) from
258 each model, so each model run contributes 10 values. The values are presented
259 this way to include the effects of interannual natural internal climate variability.

260 Over most of the domain, there is a 90% chance of experiencing a warming of at
261 least 1 C by the 2060s, and a 10% chance the warming will reach 3-4 C
262 (depending on the season). Although summer (JJA) warming is largest in most of
263 the domain, across the southern regions the differences between the seasons
264 lessens, and autumn (Sep-Oct-Nov, SON) warming matches the JJA warming.

265 3.1.2 *Forced versus natural changes in temperature*

266 The distributions in Fig. 4 have contributions from three sources: 1) the average
267 warming across models; 2) the difference in warming between models; and 3)
268 natural internal climate variability. We estimate each simulation's mean warming
269 as the mean of the 10 yearly values in the future period minus the mean of the 10
270 values in the historical period. Each simulation's natural internal climate
271 variability is estimated from the difference between the 10 individual yearly
272 values in the future period and the mean of the 10 values in the future period. This
273 method underestimates the true natural internal variability since the 10-yr average
274 in the 2060s will itself be influenced by low-frequency natural variability. The
275 error introduced by this procedure can be estimated from the historical record, as
276 outlined in the supplemental material (Section 4). Errors are modest, on the order
277 of 6-14% (Table SM2, column b). The displayed confidence intervals in Figs. 5
278 and 9 (blue bars) have been widened by these corrections.

279 Figure 5 shows the average warming, model spread, and estimate of natural
280 internal climate variability across the 11 climate regions. The annual mean model-
281 estimated warming by the 2060s (Fig. 5a green bars, degrees C) is larger than the
282 90% confidence interval of natural internal variability (blue bars) in all regions. In
283 practice, this means that the warming will be easily noticeable in the yearly
284 average. The red lines show the 90% confidence interval in estimated warming
285 across the models. The model-to-model variability is small compared to the
286 magnitude of the projected warming. Even if we knew that one of the models used
287 here was perfect and the rest wrong, it would make little difference to the
288 warming estimates.

289 The seasonal results in Fig. 5 tend to show a larger contribution from natural
290 variability, which is understandable since fewer days are being averaged over.

291 This is most pronounced in winter (DJF, Fig. 5b), where the typical scale of year-
292 to-year natural fluctuations in seasonally-averaged temperature is roughly twice
293 the expected shift in temperatures. The uncertainty across models (red line) is a
294 larger fraction of the mean warming as well. These tendencies are minimized in
295 summer (JJA, Fig. 5d), where the temperature shifts are as large compared to the
296 natural internal climate variability as seen in the yearly average.

297 *3.1.3 Changes in daily temperature*

298 Only data pooled across the BCCA and dynamical downscaling techniques (which
299 are based on the GCM's daily data) have been used for daily analyses of
300 temperature and precipitation.

301 Figure 6a shows the cumulative distribution function of daily maximum
302 temperature in July for the historical period (blue) and future period (red). An
303 error function transformation is used on the Y axis, so a Gaussian distribution
304 would form a straight line. All regions show a shift to a higher likelihood of
305 warmer daily maximum temperatures at all probability levels. The shift is smallest
306 at the warmest temperatures in the Northern and central coastal regions, perhaps
307 because of the moderating influence of cool ocean temperatures typically seen in
308 summer along California's coast. Similar curves for daily July minimum
309 temperature display more Gaussian behavior (straighter lines) and lack the
310 reduced warming along the coast (not shown).

311 By contrast, January daily minimum temperatures (Fig. 6b) show more warming
312 at the highest percentile values and little change below the median. The
313 experience on the ground in January will not be an increase in every day's
314 minimum temperature so much as the appearance of rare days with temperature
315 several degrees warmer than experienced before. While the slopes of the lines in
316 Fig. 6a (July) tend to be the same or slightly steeper in the future, indicating
317 similar or slightly reduced daily variability, the slopes of the lines in Fig. 6b (Jan)
318 tend to be flatter in the future, indicating greater daily variability in projected
319 January daily minimum (and maximum, not shown) temperatures.

320 Three-day averages of maximum daily temperature in summer (Fig. 7) are of
321 interest to the energy industry, because people are more likely to use air
322 conditioning by the third hot day. The shifts seen here are proportionally much
323 greater than in Fig. 6. Also, in all the inland locations the divergence between the
324 historical and future distribution becomes more pronounced at the warmest
325 temperatures. In the San Joaquin valley, a 3-day run of 40 C or warmer
326 temperatures is only a 1-in-100-yr occurrence in the historical simulations, but is a
327 1-in-2-yr occurrence in the future simulations. The simulated 3-day average
328 warmest temperature in the Anza-Borrego region is 46 C in the historical era, but
329 51 C in the future era. Increases along the coast are ~2 C, although even there the
330 incidence of 3-day maximum temperatures with a probability of < 0.01 in the
331 historical era increases by a factor of 10.

332 **3.2 Precipitation changes**

333 The upper panels of Fig. 8 shows the mean precipitation change (%) by the 2060s,
334 averaged across all models and downscaling techniques (45 runs total). Lower
335 panels show climatological fields for comparison. In the annual average (8a), the
336 overall tendency is for small decreases in precipitation in the southern part of the
337 state ($< 10\%$), and negligible changes in the North. The patterns by season are
338 more pronounced, with the northern part of the state experiencing wetter
339 conditions in winter that are nearly offset by drier conditions in the rest of the
340 year. The southern part of the state shows moderate fractional decreases in
341 precipitation in fall, winter and spring but a strong increase in summer
342 precipitation, which will be discussed more below. Bear in mind that California is
343 climatologically dry in the summer, so the large percentage increases found at that
344 time represent small amounts.

345 *3.2.1 Forced versus natural changes in precipitation*

346 Projected changes in seasonal-mean precipitation tend to be small compared to
347 natural internal climate variability (Fig. 9). The blue bars (90% confidence
348 interval of natural variability, tenths of mm/day) are generally an order of
349 magnitude larger than the mean model changes (green bars). At the same time, the
350 spread across the models (red lines) is typically larger than the mean model

351 change, except for the JJA decrease in precipitation across the northern part of the
352 state (Fig. 9d). However, even precipitation shifts that are small compared to the
353 inter-seasonal or inter-annual variability can be important for the long term water
354 balance of a region, especially where the water supply has little room for
355 reduction. California droughts can last 5-10 years, a long enough averaging period
356 to reduce natural variability sufficiently to expose small but systematic
357 precipitation shifts.

358 *3.2.2 The influence of downscaling technique*

359 The effect of downscaling technique on precipitation must be interpreted
360 cautiously, since not all models were downscaled with all techniques. As a group,
361 the global models downscaled with a daily technique (either dynamical or BCCA)
362 happened to be drier than the average global model by about 10 percentage points
363 in the annual average. In general, the BCCA and dynamical downscaling tend to
364 make the simulation wetter than the original global model field in all regions,
365 typically by about 9-14 percentage points. In the monsoon-influenced region in
366 the southeast of the state this tendency is so strong, the downscaling reverses the
367 sign of the global model projections.

368 The difference between downscaling techniques can be isolated by using a single
369 global model at a time. Figure 10 shows the yearly precipitation change (%)
370 simulated by the different downscaling techniques applied to the GFDL 2.1 and
371 CCSM3 global model runs, along with the global fields for comparison. The
372 downscaling methods all gave similar results for temperature (Fig. 3). However,
373 for precipitation the agreement depends on the global model. The top row of Fig.
374 10 shows the different downscaling techniques give similar results when applied
375 to the GFDL 2.1 global model. However the bottom row of Fig. 10 shows that
376 different downscaling methods give quite different results for CCSM3 (i.e., Fig.
377 10g vs. Fig. 10j), with the statistical methods most similar to the global GCM
378 signal.

379 The diversity of responses in CCSM3 can be understood, in large part, by
380 considering the details of precipitation changes in each season. Figures 11a and
381 11b show the statistical downscaling methods applied to CCSM3, while Figs. 11c

382 and 11d show the dynamical methods. Each panel shows the regions in roughly
383 geographical order, and each region has a set of 4 bars showing the climatological
384 seasonal precipitation in mm (DJF, MAM, JJA, and SON, counting the bars from
385 left to right) and the change in precipitation in mm projected by the downscaling
386 technique (colored portion of the bars). Both dynamical methods show 20-30%
387 precipitation increases in winter, while the statistical methods show increases of
388 less than 10%. Both statistical methods show MAM and SON decreases in
389 precipitation of 20-30%, while the dynamical methods show precipitation
390 decreases of <10%. In other words, the statistical and dynamical downscaling
391 technique are showing the same patterns, but with different weighting by season.
392 Depending on how the oppositely-signed tendencies are weighted, the yearly
393 average difference can be positive or negative.

394 What determines the differences between a global model trend and the
395 corresponding dynamically downscaled trend? This is addressed in Fig. 12, which
396 shows a selection (DJF and JJA) of seasonally downscaled fields driven by the
397 GFDL and CCSM3 global models. The values plotted are the differences
398 (percentage points) between the dynamically downscaled precipitation changes
399 and the changes found in the original global model. In other words, they are
400 differences of differences, and show not the future precipitation changes, but
401 rather how dynamical downscaling alters the original global model trends. In DJF,
402 the consistencies between the downscaled fields using GFDL (12a, 12e, 12i), and
403 the consistencies between the downscaled fields using CCSM3 (12c, 12g) are
404 greater than the consistencies using the same downscaling technique but a
405 different global model (12a vs. 12c, and 12e vs. 12g). This suggests that in DJF,
406 the effect of dynamical downscaling is influenced primarily by the global model
407 characteristics (e.g., the large-scale atmospheric circulation), and is less sensitive
408 to the dynamical downscaling model used.

409 In summer, in the southern half of the state, RSM (12f, 12h) tends to show much
410 wetter changes than the global models (either GFDL or CCSM3), while WRF
411 (12b, 12d) shows much drier changes than the global models (either GFDL or
412 CCSM3). The changes produced by RegCM3 lie in between (12j). This indicates
413 that summer precipitation is influenced more by the particular parameterizations
414 used by an individual dynamical downscaling model than by the global driving

415 model. In the case of RSM, this is despite the fact that spectral nudging is used to
416 keep the regional model results from diverging too greatly from the original global
417 model fields.

418 *3.2.3 Changes in daily precipitation*

419 Three-day accumulations of precipitation can be used to understand the potential
420 for flooding (e.g. Das et al. 2011), as it typically takes a few days for the soil to
421 saturate during a storm. The distributions of the maximum three-day accumulation
422 in a calendar year are shown in Fig. 13. Nearly all of California shows striking
423 increases in maximum three-day accumulations, in many instances generating
424 values far outside the historical distribution. Similar results were found in Kim
425 (2005), although that work considered snow/rain distinctions that we are not
426 examining here. Along the Northern coast, the historical distribution tops out at 80
427 mm/day with a 0.01/year chance. In the future, that same value has a greater than
428 0.1/year chance, and the distribution now extends up to 120 mm/day.

429 For planning purposes it can be useful to know whether the distributions of
430 temperature and precipitation change are related. For example, perhaps the
431 warmest projections are also the driest. However, we find no evidence that the
432 changes in temperature and precipitation distributions are linked in any season.

433 **4. Summary and Conclusions**

434 Our purpose has been to present probabilistic projections of temperature (T) and
435 precipitation (P) changes in California by the 2060s. We have included daily
436 distributions, since a number of important applications in energy demand, water
437 management, and agriculture require daily information. We focused on
438 probabilistic estimates and included natural internal climate variability, because it
439 is useful for planners to understand the range of climate projections and how those
440 compare to natural climate fluctuations.

441 We downscaled data from 16 global models using a combination of two statistical
442 techniques (BCSD and BCCA) and three nested regional climate models (WRF,
443 RCM, and RegCM3), although not all GCMs were downscaled with all

444 techniques. In total, we analyzed 9 runs with daily data, plus another 36 with
445 monthly data. As expected, the statistically downscaled fields tend to be closer to
446 the original global model simulations than do the dynamically downscaled fields.
447 All downscaling techniques were combined with equal weighting; exploring the
448 implications of weighting schemes for different downscaling techniques would be
449 a useful future extension of this work. We analyzed a historical (1985-1994) and
450 future (2060-2069) time period, using one emissions scenario, SRES A2. Our
451 estimates of natural internal variability are computed from the available 10-year
452 time slices and adjusted upwards (based on an analysis of observations) to correct
453 for the limited time period included. As appropriate given our focus on
454 applications, all model output was bias corrected.

455 We find that January-averaged temperatures as cold as any found in the historical
456 period are still seen in the 2060s, although rarer. Januarys warmer than any found
457 in the historical period are seen about 20% of the time. By contrast, cold Julys
458 (judging by current historical standards) nearly disappear by the 2060s, and the
459 hottest July average temperature found in any simulation's historical period
460 becomes a moderately cool event (15-40th percentile) by the 2060s. The warmest
461 Julys are likely to be far outside the historical experience; proportionally, the gain
462 in warm months will be much larger than the loss of cold months.

463 The downscaled T projections tend to agree across downscaling techniques. Year-
464 to-year variability in seasonally averaged T is about twice as large as the mean
465 seasonal climate warming in winter, and about half the mean warming in summer.
466 In either season, the model range in projected warming is about half the mean
467 warming signal.

468 Distributions of July daily maximum T shift more or less uniformly towards
469 warmer values, except along the Northern coast, where maximum values are less
470 changed from today. In January, the distributions are little changed below the
471 median, but show a shift towards a greater incidence of a few particularly warm
472 winter days. Distributions of the warmest 3-day average T, which drive air
473 conditioner demand, show approximately uniform shifts of +2 C across the
474 distribution.

475 Averaged across all models and downscaling techniques, weak annual mean
476 decreases in precipitation are found in the southern part of the state, and near zero
477 P change in the northern part of the state. The disagreement across models is
478 large, however. Winters tend to become wetter in the north, spring and autumn
479 show strong decreases in precipitation, and summer (when the actual values of P
480 are quite small) shows less precipitation in the north but more in the south.
481 Natural variability is typically more than an order of magnitude greater than these
482 seasonally-averaged changes, and the range of projections across models includes
483 zero, except in summer and the southern part of the state in spring.

484 The different downscaling techniques agree less for annual P changes than they do
485 for T changes. This is due to the annual P change in most models being made up
486 of competing effects, with a tendency towards more winter precipitation and less
487 spring/autumn precipitation. Different models and downscaling techniques weight
488 these competing seasonal effects differently, which can result in a positive or
489 negative change in the yearly average.

490 The dynamical downscaling techniques show larger increases in summer P in the
491 region affected by the North American monsoon than found with the statistical
492 downscaling techniques. Regional dynamical models are able to amplify monsoon
493 effects that are only coarsely represented by the GCM's, but statistical
494 downscaling has no way to sharpen these features. In general, the winter P
495 response seems more sensitive to which GCM was used, while the summer P
496 response seems more sensitive to which RCM was used. A similar finding was
497 reported in Pan et al. (2001).

498 There is a substantial increase in 3-day maximum precipitation, with peak values
499 increasing 10-50%, in agreement with Kim (2005). The increases are largest in the
500 northern part of the state, where values that have only a 0.01 probability of
501 occurrence in the historical period become 10 times more likely by the 2060s.

502 Our results have wide application to the needs of resource managers and other
503 decision makers when adapting to forthcoming climate change in California. In
504 the realm of water management, the pronounced increase in maximum 3-day
505 precipitation accumulation has implications for flooding. Likewise, these results

506 shed more light on the global model finding that California will generally
507 experience small changes in annual mean precipitation. We show that these small
508 annual mean changes are hiding much larger seasonal changes, with wetter
509 conditions in winter and sharply drier conditions in spring and autumn, although
510 even these seasonal changes are small compared to the natural variability.
511 Generally the simulations suggest that the extreme southeast of the state will
512 experience more summer rainfall as the North American monsoon intensifies,
513 although not all the different downscaling techniques agree as to the magnitude
514 and sign of this response. Probabilistic multi-model climate change evaluations
515 such as those developed here will enable a better understanding of how to adapt to
516 climate change's effects over California.

517 **Acknowledgements**

518 This work was funded by the public interest energy research (PIER) program of the California
519 Energy Commission (CEC), grant 500-07-042 to the Scripps Institution of Oceanography at UC
520 San Diego: Development of probabilistic climate projections for California. We would also like to
521 thank the global modeling groups that contributed data to the CMIP-3 archive; without their efforts
522 and generosity in sharing the data, this work would have been impossible. DWP also received
523 partial support from the International ad-hoc Detection and Attribution (IDAG) project from the
524 US Department of Energy's Office of Science, Office of Biological and Environmental Research,
525 grant DE-SC0004956 and the National Oceanic and Atmospheric Administration's Climate
526 Program Office, and the Department of Energy grant DE-SC0002000 in furtherance of work to
527 examine how daily timescale weather events and the seasonality of precipitation change to
528 accomplish low frequency, global climate changes. Partial salary support for TD from the
529 CALFED Bay-Delta Program funded-postdoctoral fellowship grant is also acknowledged.

530 **References**

- 531 Abatzoglou JT, Redmond KT, Edwards LM (2009) Classification of Regional Climate Variability
532 in the State of California. *J App Meteor Clim* 48:1527-1541
- 533 AchutaRao K, Sperber KR (2006) ENSO simulation in coupled ocean-atmosphere models: are the
534 current models better? *Clim Dyn* 27:1-15
- 535 Anderson J, Chung F, Anderson M, Brekke L, Easton D, Ejeta M, Peterson R, Snyder R (2008)
536 Progress on incorporating climate change into management of California's water resources.
537 *Climatic Change* **87 (Suppl 1)**:S91–S108, DOI 10.1007/s10584-10007-19353-10581.
- 538 Barnett TP, Pierce DW, Hidalgo HG, Bonfils C et al. (2008) Human-induced changes in the
539 hydrology of the western United States. *Science* 319:1080-1083
- 540 Bonfils C, Santer BD, Pierce DW, Hidalgo HG, Bala G, Das T, Barnett TP, Cayan DR, Doutriaux
541 C, Wood AW, Mirin A, Nozawa T (2008) Detection and Attribution of Temperature Changes in
542 the Mountainous Western United States. *J Clim* 21:6404-6424
- 543 Brekke LD, Miller NL, Bashford KE, Quinn NWT, Dracup JA (2004) Climate change impacts
544 uncertainty for water resources in the San Joaquin River Basin, California. *J Amer Water Res*
545 Assoc 40:149-164
- 546 Brekke LD, Maurer EP, Anderson JD, Dettinger MD, Townsley ES, Harrison A, Pruitt T (2009)
547 Assessing reservoir operations risk under climate change, *Water Resour. Res.*, 45, W04411,
548 doi:10.1029/2008WR006941
- 549 Caldwell P, Chin HNS, Bader DC, Bala G (2009) Evaluation of a WRF dynamical downscaling
550 simulation over California. *Clim Change* 95:499-521
- 551 Cayan D, Leurs AL, Hanemann M, Granco G, Croes B (2006) Scenarios of climate change in
552 California: An overview. California Climate Change Center report CEC-500-2005-186-SF. 53 pp.
- 553 Chen W, Jiang Z (2011) Probabilistic Projections of Climate Change over China under the SRES
554 A1B Scenario Using 28 AOGCMs. *J Clim* 24:4741-56.
- 555 Chin HNS, Caldwell PM, Bader DC (2010) Preliminary Study of California Wintertime Model
556 Wet Bias. *Mon Wea Rev* 138:3556-3571
- 557 Christensen JH, Carter TR, Rummukainen M, Amanatidis G (2007) Evaluating the performance
558 and utility of regional climate models: the PRUDENCE project. *Clim Change* 81:1-6

559 Das T, Hidalgo H, Cayan DR, Dettinger MD, Pierce DW, Bonfils C, Barnett TP, Bala G, Mirin A
560 (2009) Structure and origins of trends in hydrological measures over the western United States. *J*
561 *Hydromet*, **10**:871-892. doi:10.1175/2009JHM1095.1

562 Das T, Dettinger MD, Cayan DR, Hidalgo HG (2011) Potential increase in floods in Californian
563 Sierra Nevada under future climate projections. *Clim Change* **109** (Suppl 1):S71-94

564 Dettinger MD (2005) From climate-change spaghetti to climate-change distributions for 21st
565 century California. *San Francisco Estuary and watershed science*. 3:issue 1, article 4. 14 pp

566 Dickinson RE, Errico RM, Giorgi F, Bates GT (1989) A regional climate model for the western
567 United States. *Clim Change* 15:383-422

568 Duffy PB, Arritt RW, Coquard J, Gutowski W, Han J, Iorio J, Kim J, Leung LR, Roads J, Zeledon
569 E (2006) Simulations of present and future climates in the western United States with four nested
570 regional climate models. *J Clim* 19:873-895

571 Giorgi F, Brodeur CS, Bates GT (1994) Regional climate-change scenarios over the United States
572 produced with a nested regional climate model. *J Clim* 7:375-399

573 Hawkins E, Sunnton R (2009) The potential to narrow uncertainty in regional climate predicints.
574 *Bull Am Met Soc* 90:1095-1106.

575 Hay LE, Clark MP (2003) Use of statistically and dynamically downscaled atmospheric model
576 output for hydrologic simulations in three mountainous basins in the western United States. *J*
577 *Hydrol* 282:56-75.

578 Hayhoe K, Cayan D, Field CB, Frumhoff PC and others (2004) Emissions pathways, climate
579 change, and impacts on California. *Proc Nat Acad Sci* 101:12422-12427

580 Hidalgo HG, Dettinger MD, Cayan DR (2008) Downscaling with Constructed Analogues: Daily
581 precipitation and temperature fields over the Unites States. California Energy Commission
582 technical report CEC-500-2007-123. 48 pp.

583 Hidalgo HG, Das T, Dettinger MD, Cayan DR, Pierce DW and others (2009) Detection and
584 Attribution of Streamflow Timing Changes to Climate Change in the Western United States. *J*
585 *Clim* 22:3838-3855

586 IPCC (2007) Climate change 2007: The physical science basis. Working group I contribution to
587 the fourth assessment report of the Intergovernmental Panel on Climate Change. Cambridge
588 University Press, Cambridge, United Kingdom and New York, USA. 996 pp.

589 Kanamitsu M, Ebisuzaki W, Woollen J, Yang SK et al. (2002) NCEP-DOE AMIP-II reanalysis
590 (R-2). *Bull Am Met Soc* 83:1631-1643

591 Kanamitsu M, Kanamaru H, Cui Y, Juang H (2005) Parallel implementation of the regional
592 spectral atmospheric model. California Energy Commission technical report CEC-500-2005-014.
593 www.energy.ca.gov/2005publications/CEC-500-2005-014/CEC-500-2005-014.

594 Kim J (2001) A nested modeling study of elevation-dependent climate change signals in California
595 induced by increased atmospheric CO₂. *Geophys Res Lett* 28:2951-2954

596 Kim J (2005) A projection of the effects of the climate change induced by increased CO₂ on
597 extreme hydrologic events in the western US. *Clim Change* 68:153-168

598 Lebassi, B, González J, Fabris D, Maurer E, Miller N, Milesi C, Switzer P, Bornstein R (2009)
599 Observed 1970–2005 Cooling of Summer Daytime Temperatures in Coastal California. *J. Clim*
600 22:3558-3573.

601 Leung LR, Qian Y, Bian XD, Washington WM, Han JG, Roads JO (2004) Mid-century ensemble
602 regional climate change scenarios for the western United States. *Clim Change* 62:75-113

603 Liang XZ, Kunkel KE, Meehl GA, Jones RG, Wang JXL (2008) Regional climate models
604 downscaling analysis of general circulation models present climate biases propagation into future
605 change projections. *Geophys Res Lett* 35 doi:10.1029/2007GL032849

606 Manning LJ, Hall JW, Fowler HJ, Kilsby CG, Tebaldi C (2009), Using probabilistic climate
607 change information from a multimodel ensemble for water resources assessment, *Water Resour.*
608 *Res.*, 45, W11411, doi:10.1029/2007WR006674

609 Maurer EP, Wood AW, Adam JC (2002) A long-term hydrologically based dataset of land surface
610 fluxes and states for the conterminous United States. *J Clim* 15:3237-51

611 Maurer EP, Duffy PB (2005) Uncertainty in projections of streamflow changes due to climate
612 change in California. *Geophys Res Lett* 32, doi:10.1029/2004GL021462

613 Maurer EP (2007) Uncertainty in hydrologic impacts of climate change in the Sierra Nevada,
614 California, under two emissions scenarios. *Clim Change* 82:309-325

615 Maurer EP, Brekke L, Pruitt T, Duffy PB (2007) Fine-resolution climate change projections
616 enhance regional climate change impact studies, *Eos, Transactions, American Geophysical Union*,
617 88:504, doi:10.1029/2007EO470006

618 Maurer EP, Stewart IT, Bonfils C, Duffy PB, Cayan DR (2007) Detection, attribution, and
619 sensitivity of trends toward earlier streamflow in the Sierra Nevada, *J. Geophys Res* 112, D11118,
620 doi:10.1029/2006JD008088

621 Maurer EP, Hidalgo HG (2008) Utility of daily vs. monthly large-scale climate data: an
622 intercomparison of two statistical downscaling methods. *Hydrol. Earth Syst. Sci.*, 12:551-563.

623 Maurer EP, Hidalgo HG (2010) The utility of daily large-scale climate data in the assessment of
624 climate change impacts on daily streamflow in California. *Hydrol. Earth Syst. Sci.*, **14**:1125-1138,
625 doi:10.5194/hess-14-1125-2010

626 Meehl GA, Covey C, Delworth T, Latif M and others (2007) The WCRP CMIP3 multimodel
627 dataset - A new era in climate change research. *Bull Am Met Soc* 88:1383

628 Miller NL, Jin J, Schlegel NJ, Snyder MA et al. (2009) An analysis of simulated California climate
629 using multiple dynamical and statistical techniques. California Energy Commission report CEC-
630 500-2009-017-F, August, 2009. 47 pp.

631 Pal JS, Giorgi F, Bi XQ, Elguindi N et al. (2007) Regional climate modeling for the developing
632 world - The ICTP RegCM3 and RegCNET. *Bull Amer Met Soc* 88:1395

633 Pan Z, Christensen JH, Arritt RW, Gutowski WJ, Takle ES, Otieno F (2001) Evaluation of
634 uncertainties in regional climate change simulations. *J Geophys Res Atmos* 106:17735-17751

635 Panofsky HA, Brier GW (1968) *Some Applications of Statistics to Meteorology*, The Pennsylvania State
636 University, University Park, PA, USA, 224 pp.

637 Pennell C, Reichler T (2011) On the Effective Number of Climate Models. *J. Clim.*, 24:2358–2367.
638 doi: 10.1175/2010JCLI3814.1

639 Pierce DW, Barnett TP, Hidalgo HG, Das T et al. (2008) Attribution of Declining Western US
640 Snowpack to Human Effects. *J Clim* 21:6425-6444

641 Pierce DW, Barnett TP, Santer BD, Gleckler PJ (2009) Selecting global climate models for
642 regional climate change studies. *Proc Nat Acad Sci* 106:8441-8446

643 Skamarock WC, Klemp JB, Duidhia J, Gill DO, Barker DM, Duda MG, Huang X-Y, Wang W,
644 Powers JG (2008): A description of the Advanced Research WRF Version 3. NCAR technical note
645 NCAR/TN-475+STR. 125 pp.

646 Snyder MA, Bell JL, Sloan LC, Duffy PB, Govindasamy B (2002) Climate responses to a
647 doubling of atmospheric carbon dioxide for a climatically vulnerable region. *Geophys Res Lett*
648 29:4

649 Snyder MA, Sloan LC, Diffenbaugh NS, Bell JL (2003) Future climate change and upwelling in
650 the California Current. *Geophys. Res Lett* 30:1823

651 Snyder MA, Sloan LC (2005) Transient future climate over the western United States using a
652 regional climate model. *Earth Interactions* v. 9 paper 11.

653 Wood AW, Maurer EP, Kumar A, Lettenmaier DP (2002) Long-range experimental hydrologic
654 forecasting for the eastern United States. *J Geophys Res Atmos* 107 , doi:10.1029/2001jd000659

655 Wood AW, Leung LR, Sridhar V, Lettenmaier DP (2004) Hydrologic implications of dynamical
656 and statistical approaches to downscaling climate model outputs. *Clim Change* 62:189-216

657 **Table 1**

GCM	Institution	BCSD	BCCA	WRF	RSM	RegCM3
BCCR BCM 2.0	Bjerknes Centre Clim. Res., Bergen, Norway	1				
CCCMA CGCM3.1	Canadian Centre, Victoria, B.C., Canada	5				
CNRM CM3	Meteo-France, Toulouse, France	1	1			
CSIRO MK3.0	CSIRO Atmos. Res., Melbourne, Australia	1				
GFDL CM2.0	Geophys. Fluid Dyn. Lab, Princeton, NJ, USA	1				
GFDL CM2.1	Geophys. Fluid Dyn. Lab, Princeton, NJ, USA	1	1	1	1	1
GISS e_r	NASA/Goddard Inst. Space Studies, N.Y., USA	1				
INMCM 3.0	Inst. Num. Mathematics, Moscow, Russia	1				
IPSL CM4	Inst. Pierre Simon Laplace, Paris, France	1				
MIROC 3.2 medres	Center Climate Sys. Res., Tokyo, Japan	3				
MIUB ECHO-G	Meteor. Inst. U. Bonn, Bonn, Germany	3				
MPI-ECHAM5	Max Planck Inst. Meteor., Hamburg, Germany	3				
MRI CGCM2.3.2	Meteor. Res. Inst., Tsukuba, Ibaraki, Japan	5				
NCAR CCSM3	Nat. Center Atmos. Res., Boulder, CO, USA	4	1	1	1	
NCAR PCM1	Nat. Center Atmos. Res., Boulder, CO, USA	4	1			
UKMO HadCM3	UK Met Office, Exeter, Devon, UK	1				

658

659 Table 1. The global general circulation models (GCMs) used in this project, their
660 originating institution, and the number of ensemble members downscaled by the
661 indicated method. BCSD: bias correction with spatial disaggregation; BCCA: bias
662 correction with constructed analogues; WRF: weather research forecast model;
663 RSM: regional spectral model; RegCM3: Regional climate model version 3.

664

665 Figure 1. Upper: temperature change ($^{\circ}\text{C}$) from years 1985-94 to 2060-69. The seasonally-
 666 averaged data from all models and downscaling techniques was averaged across models to
 667 generate the values. The regions used in this work are also shown. Lower: temperature climatology
 668 ($^{\circ}\text{C}$) averaged across the models, and observed annual mean for comparison (lower right).

669

670 Figure 2. Correspondence between percentiles of monthly-averaged temperature in the historical
 671 period (x axis) and future period (y axis), for January (left) and July (right). For instance, the blue
 672 cross in panel a for the Sacramento/Central valley shows that the 50th percentile temperature in the
 673 historical period will become the 17th percentile value in the 2060s. The grey line shows what the
 674 result would be if there were no changes in the distributions. The regions are plotted in roughly
 675 geographic order (Northwest locations in the top left, etc.). The figure is made with monthly data
 676 from all 45 model runs.

Figure 3. Yearly temperature change (C) (2060-2069 minus 1985-1994) from each downscaling technique applied to the GFDL 2.1 global model (upper) and CCSM3 global model (lower). The yearly temperature changes from the global models are shown in panels f and k, for comparison.

681

682 Figure 4. Probability of a temperature change of the indicated value or greater, by region and
 683 season. The regions are plotted in roughly geographic order (Northwest locations in the top left,
 684 etc.). Monthly data from all 45 runs is used to make the figure.

685

686 Figure 5. A comparison of the contribution of natural internal climate variability and model
 687 uncertainty to yearly and seasonally averaged projected temperature changes by the 2060s. Blue
 688 bars show the 90% confidence interval of natural internal climate variability in near surface air
 689 temperature (C) estimated across all models. Green bars show the mean model warming projected
 690 in the period 2060-69. The red line shows the 90% confidence interval in the projected warming
 691 across models. Note that each inset plot has a different scale for the Y axis, in degrees C. Monthly
 692 data from all 45 runs is used to make the figure.

693

694

695

696

697

698

699

700

Figure 6. Cumulative distribution functions of July daily maximum temperature (left) and January daily minimum temperature (right) across the regions (plotted roughly geographically). The Y axis shows the probability (zero to one) of experiencing the indicated temperature or lower on any particular day. Results from the historical run are in blue; the future run is in red. Large solid dots show where the two curves are different at the 95% significance level, evaluated using a bootstrap technique. Open circles indicate statistically indistinguishable values. Data from the 9 runs with daily data was used to make the figure.

701

702 Figure 7. Cumulative distribution functions of the highest 3-day average temperature in the year.
 703 The Y axis shows the probability (zero to one) of having the warmest 3 days in a year be the
 704 indicated temperature or lower. Results from the historical run are in blue; the future run is in red.
 705 Panels are plotted roughly geographically. Large solid dots show where the two curves are
 706 different at the 95% significance level evaluated using a bootstrap technique. Data from the 9 runs
 707 with daily data was used to make the figure.

/home/pierce/projects/cec_scenarios/data/plot_CA_tracker_region_dels_v26.R Fri Feb 17 09:10:39 2012

708
 709 Figure 8. Upper panels: Precipitation change (%), mean over the period 2060-69 compared to
 710 mean over the period 1985-94. Data from all models and downscaling techniques was averaged to
 711 generate the values. Lower panels: model climatological precipitation (tenths of mm/day), and
 712 annual average from observations for comparison (lower right).

/home/pierce/projects/cec_scenarios/data/make_dists_by_region_v4.R Sat Feb 18 10:17:53 2012

713

714 Figure 9. A comparison of the contribution of natural internal climate variability and model
 715 uncertainty to yearly and seasonally averaged precipitation changes. Blue bars show the 90%
 716 confidence interval of natural internal climate variability in seasonally averaged precipitation
 717 (tenths of mm/day) estimated across all models, for the period 2060-69. Green bars show the mean
 718 model precipitation change projected in the period 2060-69. The red line shows the 90%
 719 confidence interval in the projected precipitation change across models. Note that each inset plot
 720 has a different scale for the Y axis. Monthly data from all 45 runs is used to make the figure.

721

722 Figure 10. Yearly precipitation change (% 2060-2069 compared to 1985-1994) from each
 723 downscaling technique applied to the GFDL 2.1 (top row) and CCSM3 (bottom row) global
 724 models. The yearly precipitation changes from the global models are shown in panels f and k, for
 725 comparison. Since the effect of downscaling on the global model fields is being illustrated, only
 726 one BCSD ensemble member is shown, the one corresponding to the illustrated global model and
 727 used for the dynamical downscaling.

728

729 Figure 11. Changes in precipitation for the different downscaling methods applied to the CCSM3
 730 global model. In each panel a-d, the subpanels show the precipitation changes by region, arranged
 731 roughly geographically. The bars show each region's seasonal precipitation (mm) in DJF, MAM,
 732 JJA, and SON (left to right) in the future and historical periods. The difference between the future
 733 and historical precipitation is colored, with the color determined by the percentage change using
 734 the same scale as Fig. 10 (yellows/oranges show less precipitation, blue/green show more
 735 precipitation). Note that every set of bars has a different Y axis, in mm.

Figure 12. Difference (percentage points) between the change in seasonal precipitation projected by the dynamically downscaled simulations and the change found in the original global model (GFDL 2.1 or CCSM3, as labeled). Only winter (DJF) and summer (JJA) fields are shown.

740

741 Figure 13. Cumulative distribution functions (CDFs) of the maximum 3-day mean precipitation in
 742 a calendar year. Regions are plotted roughly geographically. Y axis is probability (0-1) of
 743 experiencing the indicated average 3-day precipitation rate (mm/day), or lower. Large solid dots
 744 show where the two curves are different at the 95% significance level, evaluated using a bootstrap
 745 technique. Open circles indicate statistically indistinguishable values. Data from the 9 runs with
 746 daily data was used to make the figure.

747

Supplemental Material for

748 Probabilistic estimates of future changes in 749 California temperature and precipitation using 750 statistical and dynamical downscaling

751 David W. Pierce^{1,*}, Tapash Das^{1,6}, Daniel R. Cayan¹, Edwin P. Maurer², Norman
752 Miller³, Yan Bao³, M. Kanamitsu¹, Kei Yoshimura¹, Mark A. Snyder⁴, Lisa C.
753 Sloan⁴, Guido Franco⁵, Mary Tyree¹

754 1. Descriptions of the Regional Climate Models (RCMs)

755 1.1 Regional Climate Model version 3 (RegCM3)

756 RegCM3 is a third-generation regional-scale climate model derived from the
757 National Center for Atmospheric Research-Pennsylvania State (NCAR-PSU)
758 MM5 mesoscale model (Pal et al. 2007). RegCM3 has the same dynamical core as
759 MM5, the CCM3 radiative transfer package, and the Biosphere-Atmosphere
760 Transfer Scheme (BATS) land surface model (Dickinson et al., 1986; Giorgi et al.,
761 2003). RegCM has been validated against observations of modern-day climate in
762 multiple domains, and does well in simulating the spatial and temporal climate
763 features of California (Snyder et al. 2002, Bell et al. 2004). For this study
764 RegCM3 was configured with the Holtslag boundary layer scheme (Holtslag et
765 al., 1990), Grell cumulus scheme (Grell, 1993) with the Fritsch and Chappell
766 closure scheme (Fritsch and Chappell, 1980), and the Zeng (1998) ocean flux
767 parameterization. The model domain is centered over California with a horizontal
768 resolution of 10 km and 18 levels in the vertical.

769 1.2 Weather Research and Forecasting model (WRF)

770 We use a version of NCAR WRF version 3 coupled to the community land
771 surface model version 3.5 (CLM3.5; Oleson et al. 2004), referred to as “WRF-
772 CLM3” in Miller et al. (2009). The combination has an advanced land surface
773 scheme with sub-grid representation for snow and vegetation, lateral hydrologic

774 flow capability, and the potential for time-evolving plant functional types. The
775 WRF model is set up with 10 km horizontal resolution, and uses the Kain-Fritsch
776 convection parameterization for cumulus clouds (Kain and Fritsch 1993), the
777 Yonsei University (YSU) planetary boundary layer (PBL) scheme (Hong and Pan
778 1996), and the Medium Range Forecast Model turbulence closure scheme (Mellor
779 and Yamada 1982). The microphysics package used here is the WRF Single-
780 Moment 3-class (WSM3) scheme (Hong et al. 2004), and the Rapid Radiative
781 Transfer Model (RRTM) based on Mlawer et al. (1997) is used for describing
782 longwave radiation transfer within the atmosphere and to the surface, and the
783 shortwave scheme developed by Dudhia (1989). Dynamical downscaling using
784 WRF has been evaluated over the state of California (Caldwell et al. 2009), and
785 WRF coupled to CLM3.5 has been used to show that changes in vegetation can
786 have appreciable effects on local climate (Subin et al. 2011).

787 *1.3 Regional Spectral Model (RSM)*

788 The version of the regional spectral model (RSM) used here is a development of
789 the National Centers for Environmental Prediction (NCEP) global spectral model
790 (GSM). The original regional code has been modified to have greater flexibility
791 and increased efficiency (Kanamitsu et al., 2005). The RSM uses a two-
792 dimensional spectral decomposition, and is implemented with so-called “spectral
793 nudging”, i.e., relaxation towards the low-frequency components of the global
794 simulation over the regional domain (Kanamitsu and Kanamitsu 2007). The
795 configuration used here is similar to that used to generate the 10-km California
796 Reanalysis Downscaling (CaRD10) data set (Kanamitsu and Kanamitsu, 2007). A
797 scale-selective bias correction (SSBC) was used during these runs (Kanamitsu and
798 Kanamitsu 2007). The Noah land surface model with four soil layers was used,
799 and cloud water and cloudiness are implemented as prognostic variables (Tiedtke
800 1993; Iacobellis and Sommerville 2000).

801 **2. Statistical downscaling methods**

802 We use two different statistical downscaling techniques. Both operate on bias-
803 corrected GCM data; the bias correction (BC) procedure is described in section

804 2.3. The BCCA technique downscales daily global model data, while the BCSD
805 technique downscales monthly global model data.

806 *2.1 Bias Correction with Spatial Disaggregation (BCSD)*

807 BCSD (Wood et al. 2002, 2004) generates daily, fine-resolution ($1/8^\circ \times 1/8^\circ$ in this
808 implementation) fields from monthly, bias-corrected GCM data by expressing
809 these coarse (GCM-scale) monthly values of average temperature and
810 precipitation as anomalies relative to a historical climatology. The monthly GCM
811 anomalies are interpolated onto the fine-scale grid, then applied, by offsetting (for
812 temperature) or scaling (for precipitation), to the long term mean at the fine scale.
813 This produces a fine scale monthly downscaled value. To generate daily
814 variability within each month an analogue month from the historical observations
815 is selected, with the selected month being the same month of the year as the data
816 being downscaled. The daily observed data for the analogue month on the fine-
817 scale grid is then offset (for temperature) or scaled (for precipitation) so that each
818 grid cell's monthly mean matches the monthly downscaled value. Since analogue
819 months from the historical period are used to generate the daily sequences, we do
820 not analyze BCSD-generated distributions of daily future climate variables. BCSD
821 downscaling is used, for example, by Hayhoe et al. (2004), Maurer (2007), and
822 Vicuna et al. (2007).

823 *2.2 Bias Correction with Constructed Analogues (BCCA)*

824 BCCA uses bias correction along with downscaling of daily GCM fields via
825 constructed analogues (Hidalgo et al., 2008; Maurer et al. 2010). BCCA is
826 therefore the CANA method described by Miller et al. (2009) along with a BC
827 step applied to the GCM temperature and precipitation fields. The constructed
828 analogue technique starts with a library of daily historical observations on a $1/8^\circ \times$
829 $1/8^\circ$ grid. This fine scale data is coarsened to the GCM grid, and the 30 best
830 matches (analogues) between the GCM fields for that day (including in the library
831 observed days within a ± 45 day window of the target date) and the coarsened
832 observations are computed. The 30 analogues are combined, using the strength of
833 their correspondence to the GCM grid as weights, into a GCM-scale constructed

834 analogue. The same linear combination is then applied to the fine scale observed
835 data to obtain the final downscaled data for a day.

836 **3. Bias correction procedure**

837 The output of the GCMs was bias corrected to observations (Maurer et al. 2002)
838 before statistical downscaling, while the output of the dynamical RCMs was bias
839 corrected after being generated. In general, before bias correction the RCMs tend
840 to display 10-20% drier than observed conditions in the Northern part of the state
841 in winter, 20-50% too wet conditions in the inland desert regions in winter, 10-
842 20% wetter conditions than observed in the Northern part of the state in spring,
843 and an overall warm bias of 0.1-2.0 C throughout the year.

844 BCSD starts with monthly GCM data, which we bias correct using the quantile-
845 mapping technique (Panofsky and Brier, 1968), described in Maurer (2007), based
846 on Wood et al. (2002, 2004). The mapping parameters are determined for each
847 month by comparing the model results to the observations over the
848 model/observations overlap period 1950-1999, and then are applied to the future
849 period. The assumption is that the biases are unchanged in the future (cf. Liang et
850 al. 2008). For bias correcting GCM output, Wood et al. (2004) suggest as long a
851 historical period as possible be used to characterize monthly GCM biases, with
852 ranges for robust error correction from 20-50 years (or longer). For temperature,
853 the linear trend from the GCM output (interpolated to the fine scale grid) was
854 removed at each point before the BC procedure was applied, and then added back
855 in afterwards. The reason for this is explained by Wood et al. (2004): as
856 temperatures rise in the future they are found more frequently outside the historic
857 range, requiring excessive extrapolation during the quantile mapping.
858 Precipitation, with typically much greater interannual variability than temperature,
859 does not generally experience trends that exhibit this problem during remapping,
860 so the trend removal and replacement was not applied. In theory, this procedure
861 has the advantage that the final result preserves the original trend in the global
862 model, but the disadvantage that the resulting trend is essentially that of the
863 interpolated global model. In practice, the application of bias correction can still
864 modify the original global model trends for reasons explained below.

865 The BCCA and RCM data are daily. We bias correct the daily data using a similar
866 quantile mapping technique, described in Maurer et al. (2010). The historical
867 period used for the monthly BCCA downscaling was the 50-yr span 1950-1999,
868 but only the 10-yr period 1984-1995 is available for the RCM data. When bias
869 correcting daily (instead of monthly) data, 10 years is adequate, as 10 years of
870 daily information (~3652 time steps) provides considerably more samples than 50
871 years of monthly information (600 time steps) (Maurer et al., manuscript in
872 preparation; see also Chen et al. 2011).

873 In contrast to BCSD, the global trend was not removed and then reapplied for the
874 BCCA and RCM data, since the motivation for trend removal and replacement
875 described above is not as strong for daily data. For example, since a large portion
876 of the trend in daily temperatures is due to more frequent warm temperatures (as
877 opposed to relatively few record hot temperatures) (Dettinger et al. 2004), which
878 are represented in the historic period, the trend removal and replacement
879 procedure is less necessary. This also means that the trend in these data sets is free
880 to differ from the GCM trend. Since the basic assumption of downscaling is that it
881 adds regionalized information to the global signal, this is a desirable
882 characteristic.

883 However, the bias correction itself can modify the global trend (Hagemann et al.
884 2011). Table SM1 illustrates this for July average daily temperature at one grid
885 point. Bias correction modifies the variance of the GCM output, since GCM
886 simulations inevitably contain biases in variance, skew, and higher moments. The
887 historical mapping is applied to future projections, so this process changes the
888 statistical properties of the GCM projections. This table shows that when bias
889 correction increases the standard deviation of the monthly data, then the low-
890 frequency trend increases as well; when BC decreases the standard deviation, the
891 trend decreases. In essence, the procedure assumes that errors in the amplitude of
892 variability apply equally on all timescales, from daily to the secular trend.
893 Whether the trend modification is appropriate given GCM errors in simulating
894 variability or if the raw simulated trend should be preserved through the
895 downscaling procedure is an open question.

896 **4. Errors in the estimation of natural internal climate variability**

897 The procedure described in the main text section 3.1.2 underestimates the value of
898 natural internal climate variability since it is based the spread around the 10-yr
899 average during the 2060's, but the 10-yr average itself will be affected by low-
900 frequency natural internal climate variability. The size of this effect can be
901 estimated from the historical record, assuming that future changes in the spectral
902 structure of natural variability will be modest.

903 Using the technique described in Appendix A of Barnett & Pierce (2008)
904 (transforming an observed time series to frequency space, randomizing the phases,
905 and transforming back while taking sampling uncertainty in the estimate of the
906 spectral amplitudes into account), we constructed 200 random time series for each
907 variable (T, P) and each California region. Observed time series were computed
908 from Hamlet and Lettenmaier (2005). Each random time series, by construction,
909 has a mean and spectrum that is indistinguishable from observations (within
910 sampling uncertainty). We then used the 200 random time series to calculate the
911 natural variability as done in section 3.1.2 (in a 10-yr chunk) and compared it to
912 the variability directly calculated from the full time series.

913 For temperature, the true 90% confidence interval was 6-20% wider than
914 calculated as in the manuscript; for precipitation, the true 90% C.I. was 5-25%
915 wider (Table SM2). This overstates the error in for temperature, since all
916 California regions show a strong warming over the observed time period that has
917 been shown to be anthropogenic in origin (e.g., Bonfils et al., 2008). Using a
918 simple linear detrending for temperature and recomputing, the true C.I. for
919 temperature was 6-14% wider than indicated by the method used in the
920 manuscript. Figures 5 and 9 in the main text have been corrected to show this
921 wider range for natural internal variability (the blue bars).

922 **Supplemental Material References**

923 Barnett TB, Pierce DW (2008) When will Lake Mead go dry? Water Resources Res 44:W03201
924 doi:10.1029/2007WR006704

- 925 Bonfils C, Santer BD, Pierce DW, Hidalgo HG, Bala G, Das T, Barnett TP, Cayan DR, Doutriaux
926 C, Wood AW, Mirin A, Nozawa T (2008) Detection and attribution of temperature changes in the
927 mountainous western United States. *J Climate* 21:6404-6424
- 928 Chen C, Haerter JO, Hagemann S, Piani C (2011) On the contribution of statistical bias correction
929 to the uncertainty in the projected hydrological cycle. *Geophys Res Lett* 38:L20403
- 930 Dettinger MD, Cayan DR, Meyer M, Jeton AE (2004) Simulated hydrologic responses to climate
931 variations and change in the Merced, Carson, and American River basins, Sierra Nevada,
932 California, 1900-2099. *Clim Change* 62:283-317.
- 933 Dickinson RE, Kennedy PJ, Henderson-Sellers A, Wilson M (1986) Biosphere-atmosphere
934 transfer scheme (BATS) for the NCAR Community Climate Model, Tech. Rep. NCAR/TN-
935 275+STR, National Center for Atmospheric Research
- 936 Dudhia J (1989) Numerical study of convection observed during the winter monsoon experiment
937 using a mesoscale two-dimensional model. *J Atmo Sci* 46:3077-3107
- 938 Fritsch JM, Chappell CF (1980) Numerical prediction of convectively driven mesoscale pressure
939 systems. part I: Convective parameterization. *J Atmos Sci* 37:1722-1733
- 940 Giorgi F, Bi XQ, Qian Y (2003) Indirect vs. direct effects of anthropogenic sulfate on the climate
941 of east asia as simulated with a regional coupled climate-chemistry/aerosol model. *Clim Change*
942 58:345-376
- 943 Grell G (1993) Prognostic evaluation of assumptions used by cumulus parameterizations. *Mon*
944 *Wea Rev* 121:764-787
- 945 Hagemann S, C Chen, JO Haerter, J Heinke, D Gerten, C Piani (2011) Impact of a Statistical Bias
946 Correction on the Projected Hydrological Changes Obtained from Three GCMs and Two
947 Hydrology Models. *J Hydromet* 12:556-578
- 948 Hamlet AF, Lettenmaier DP (2005) Production of temporally consistent gridded precipitation and
949 temperature fields for the continental United States. *J Hydromet* 6:330-336
- 950 Hidalgo HG, Dettinger MD, Cayan DR (2008) Downscaling with Constructed Analogues: Daily
951 precipitation and temperature fields over the Unites States. California Energy Commission
952 technical report CEC-500-2007-123. 48 pp.
- 953 Holtslag, AAM, de Bruijn EIF, Pan H-L (1990) A high resolution air mass transformation model
954 for short-range weather forecasting. *Mon Wea Rev* 118:1561-1575
- 955 Hong SY, Pan HL (1996) Nonlocal boundary layer vertical diffusion in a Medium-Range Forecast
956 Model. *Mon Wea Rev* 124:2322-2339

957 Hong SY, Dudhia J, Chen SH (2004) A revised approach to ice microphysical processes for the
958 bulk parameterization of clouds and precipitation. *Mon Wea Rev* 132:103-120

959 Iacobellis SF, Somerville RCJ (2000) Implications of microphysics for cloud-radiation
960 parameterizations: Lessons from TOGA COARE. *J Atmos Sci* 57:161-183

961 Kain JS and Fritsch JM (1993) Convective parameterization for mesoscale models: The Kain-
962 Fritsch scheme. *Meteor Monogr No. 24, Amer. Meteor. Soc.*, 165-170.

963 Kanamaru H, Kanamitsu M (2007) Scale-selective bias correction in a downscaling of global
964 analysis using a regional model. *Mon Wea Rev* 135:334-350

965 Kanamitsu M, Kanamaru H, Cui Y, Juang H (2005) Parallel implementation of the regional
966 spectral atmospheric model. California Energy Commission technical report CEC-500-2005-014.
967 www.energy.ca.gov/2005publications/CEC-500-2005-014/CEC-500-2005-014.

968 Kanamitsu M, Kanamaru H (2007) Fifty-seven-year California Reanalysis Downscaling at 10 km
969 (CaRD10). Part I: System detail and validation with observations. *J Clim* 20:5553-5571

970 Liang XZ, Kunkel KE, Meehl GA, Jones RG, Wang JXL (2008) Regional climate models
971 downscaling analysis of general circulation models present climate biases propagation into future
972 change projections. *Geophys Res Lett* 35 doi:10.1029/2007GL032849

973 Maurer EP, Wood AW, Adam JC (2002) A long-term hydrologically based dataset of land surface
974 fluxes and states for the conterminous United States. *J Clim* 15:3237-51

975 Maurer EP, Brekke L, Pruitt T, Duffy PB (2007) Fine-resolution climate change projections
976 enhance regional climate change impact studies, *Eos, Transactions, American Geophysical Union*,
977 88:504, doi:10.1029/2007EO470006

978 Maurer EP, Hidalgo HG, Das T, Dettinger MD, Cayan DR (2010) The utility of daily large-scale
979 climate data in the assessment of climate change impacts on daily streamflow in California.
980 *Hydrol. Earth Syst. Sci.*, **14**:1125-1138, doi:10.5194/hess-14-1125-2010

981 Mellor GL, Yamada T (1982) Development of a turbulence closure-model for geophysical fluid
982 problems. *Rev Geophys* 20:851-875

983 Miller NL, Jin J, Schlegel NJ, Snyder MA et al. (2009) An analysis of simulated California climate
984 using multiple dynamical and statistical techniques. California Energy Commission report CEC-
985 500-2009-017-F, August, 2009. 47 pp.

986 Mlawer EJ, Taubman SJ, Brown PD, Iacono MJ, Clough SA (1997) Radiative transfer for
987 inhomogeneous atmospheres: RRTM, a validated correlated-k model for the longwave. *J Geophys*
988 *Res Atmos* 102:16663-16682

- 989 Oleson KW, Dai Y, Bonan G, Bosilovich M et al. (2004) Technical description of the
990 community land model (CLM). NCAR Tech. note NCAR/TN-461+STR. 186 pp.
- 991 Pal JS, Giorgi F, Bi XQ, Elguindi N et al. (2007) Regional climate modeling for the developing
992 world - The ICTP RegCM3 and RegCNET. Bull Amer Met Soc 88:1395
- 993 Panofsky HA. Brier GW (1968) Some Applications of Statistics to Meteorology, The Pennsylvania State
994 University, University Park, PA, USA, 224 pp.
- 995 Subin ZM, Riley WJ, Jin J, Christianson DS, Torn MS, Kueppers LM (2011) Ecosystem feedbacks
996 to climate change in California: Development, testing, and analysis using a coupled regional
997 atmosphere and land-surface model (WRF3-CLM3.5). *Earth Interactions*. 15: 1-38. doi:
998 10.1175/2010EI331.1
- 999 Tiedtke M (1993) Representation of clouds in large-scale models. Mon Wea Rev 121:3040-3061
- 1000 Wood AW, Maurer EP, Kumar A, Lettenmaier DP (2002) Long-range experimental hydrologic
1001 forecasting for the eastern United States. J Geophys Res Atmos 107 , doi:10.1029/2001jd000659
- 1002 Wood AW, Leung LR, Sridhar V, Lettenmaier DP (2004) Hydrologic implications of dynamical
1003 and statistical approaches to downscaling climate model outputs. Clim Change 62:189-216
- 1004 Zeng XB, Zhao M, Dickinson RE (1998) Intercomparison of bulk aerodynamic algorithms for the
1005 computation of sea surface fluxes using TOGA COARE and TAO data. J Clim 11:2628-2644

1006 **Table SM1**

Statistic	NCAR	CNRM	NCAR	GFDL
	CCSM3	CM3	PCM1	CM2.1
σ pre bias correction	0.84	0.66	0.49	0.73
σ post bias correction	0.67	0.85	0.50	0.60
ΔT pre bias correction	2.7	1.7	1.3	2.3
ΔT post bias correction	2.2	2.3	1.3	1.9

1007

1008 Table SM1. An example of the effect of bias correction on the standard deviation
1009 (σ) of average daily July temperature (for a future period of 2040-2069) on the
1010 projected changes in temperature (ΔT) between the future period and a historic
1011 baseline of 1950-1999 for a single grid point located at latitude 39, longitude -121,
1012 over northern California.

1013 **Table SM2**

Region	a) T error	b) T error (detrended)	c) P error
S. California coast	20%	13%	9%
Anza-Borrego	8%	6%	25%
San Joaquin valley	14%	8%	9%
Sierra Nevada	7%	7%	5%
Northeast California	6%	8%	9%
N. California coast	18%	14%	6%
Central N. California	10%	10%	5%
Central coast	19%	8%	6%
S. California Mtns.	11%	9%	10%
Inland Empire	12%	7%	13%
Sac/Central Valley	19%	6%	9%

1014

1015 Table SM2. Estimated error in the 90% confidence interval of natural internal
 1016 climate variability obtained when taking the average with respect to a 10-year
 1017 period rather than using the entire period of record. Values are based on
 1018 observations over the period 1915-2004. Column a) temperature; b) temperature,
 1019 but detrending the temperature record first to remove anthropogenic warming; c)
 1020 precipitation. See supplemental material text (section 4) for details.

1021