

1 **Mean surface runoff insensitive to warming**  
2 **in a key Mediterranean-type climate:**  
3 **A case study of the Los Angeles Region**  
4  
5

6 Marla Schwartz<sup>1</sup>  
7 University of California, Los Angeles  
8

9 Alex Hall  
10 University of California, Los Angeles  
11

12 Fengpeng Sun  
13 University of California, Los Angeles  
14  
15  
16  
17  
18  
19  
20  
21  
22  
23  
24  
25  
26  
27  
28  
29  
30  
31  
32  
33  
34  
35  
36  
37  
38

---

<sup>1</sup> *Corresponding author address: Marla Schwartz, Math Science Bldg Rm 7229, UCLA, Department of Atmospheric and Oceanic Sciences, Los Angeles CA 90095.*  
Email: marla@atmos.ucla.edu

39  
40  
41  
42  
43  
44  
45  
46  
47  
48  
49  
50  
51  
52  
53  
54  
55  
56  
57  
58  
59  
60  
61

## Abstract

This paper investigates the sensitivity of surface hydrology in the Los Angeles region to climate change. Using dynamical downscaling, we produce 2-km resolution regional projections for the mid-21<sup>st</sup> century (2041-2060) under the “business-as-usual” (RCP8.5) forcing scenario for five global climate models in the Fifth Coupled Model Intercomparison Project. Future projections are compared to a validated reanalysis-driven simulation of a baseline period (1981-2000) to quantify surface hydrology changes. Precipitation changes are likely to be small and are within the range of baseline interannual variability. Runoff changes are strongly controlled by precipitation changes, suggesting temperature-driven changes in actual evapotranspiration are small. A series of temperature sensitivity experiments are performed in which a land surface model is forced by the meteorology of the baseline period, but with uniform near-surface air temperature increases of 2°, 4° and 6° C. Results from these idealized experiments reveal annual mean actual evapotranspiration and runoff are nearly insensitive to warming. This insensitivity is an artifact of the region’s Mediterranean-type climate: Because the warm season receives almost no precipitation, the strongest warming-induced potential evapotranspiration enhancement coincides with dry soils, severely constraining actual evapotranspiration increases. Surface hydrology in other Mediterranean climate regions may respond similarly. This result greatly mitigates a potential vulnerability of water resources to a changing climate in an important semi-arid region of the world. It also reveals that a regional climate change adaptation strategy relying on local water resources is a viable one.

## 62 **1. Introduction**

63

64 Mediterranean-type climate zones (California, lands around the Mediterranean Sea, central  
65 Chile, southwestern South Africa, and southwestern and southern Australia) are characterized by  
66 warm, dry summers and cool, rainy winters (Myers et al. 2000; Cowling et al. 2005; Kottek et al.  
67 2006). The floras of these regions are among the world's richest, harboring almost 20% of all  
68 known vascular plant species despite occupying less than 5% of the earth's surface (Cowling et  
69 al. 1996). Mediterranean-type climate regions have also been recognized as particularly  
70 threatened by global climate change (IPCC 2014).

71

72 A potentially unique surface hydrological response to climate change may arise from the  
73 seasonality of Mediterranean-type hydrology. Projected temperature increases, along with  
74 increased downward longwave radiation from greater concentrations of greenhouse gases, would  
75 enhance potential evapotranspiration (PET). The enhancement is especially large in the warm  
76 months, due to the non-linearity of the Clausius-Clayeron relationship. However, because rain  
77 comes during the cool months, soil moisture levels are low during the warm months. As a result,  
78 the time of the strongest PET enhancement may coincide with the driest soils. Thus it is unclear  
79 whether actual evapotranspiration (AET) will respond strongly to warming. Surface runoff may  
80 likewise be only weakly affected by warming. Therefore, it is important to investigate how  
81 climate-change induced temperature and precipitation changes will impact surface hydrology in  
82 Mediterranean-type climate regions.

83

84 This paper explores the hydrologic response of California’s Los Angeles region as a case study.  
85 Previous studies have documented observed changes in California’s hydro-climate over the past  
86 few decades, as well as potential impacts in hydrology and water resources in the western United  
87 States (Roos 1991; Hamlet et al. 2005; Maurer 2007; Barnett et al. 2008; Bates et al. 2008; Adam  
88 et al. 2009; Kapnick and Hall 2010). However, a high-resolution assessment of the response of  
89 surface hydrology in the Los Angeles region to climate change has not been done before.

90  
91 This study is informative due to its implications for other Mediterranean-type climate zones, and  
92 it is crucial for informed local water resources planning. The Greater Los Angeles region  
93 depends on numerous sources of fresh water, both imported and local. Though the majority of  
94 Los Angeles’ water is imported via the Los Angeles and Colorado River Aqueducts, local water  
95 accounted for 11% of the Los Angeles Department of Water and Power’s water supply from  
96 2005-2010 (Blanco et al. 2012). In some nearby cities within the Greater Los Angeles region,  
97 local water sources contribute an even larger portion. For example, local water supplied about  
98 40% of the overall water demand between 1995 and 2009 in the city of Camarillo (City of  
99 Camarillo 2010) and 55% of the water demand in Long Beach for 2010 (Long Beach Water  
100 Department 2010).

101  
102 Cities in Mediterranean-type climates outside of California also rely heavily on local water,  
103 including Cape Town, South Africa, which chiefly depends on dams in the mountains of the  
104 southwestern Cape for both industrial and domestic water supply (Ziervogel et al. 2010).  
105 Adelaide, Australia sources water from neighboring catchments in the Mount Lofty Ranges and  
106 approximately half of Adelaide’s demand has been supplied from the nearby Myponga, Mount

107 Bold, and Happy Valley reservoirs (Paton et al. 2013). In central Chile, snowpack accumulated  
108 in the nearby central Andes represents a critical resource for local irrigation, consumption,  
109 industries and hydroelectric generation (Masiokas et al. 2006).

110

111 General circulation models (GCMs) provide insight into future climate trends, but their coarse  
112 resolution fails to capture climatic variables at a scale necessary for regional-scale analysis  
113 (Giorgi and Mearns, 1991). The latest generation of GCMs in the World Climate Research  
114 Programme's Coupled Model Intercomparison Project Phase 5 (CMIP5; Taylor et al. 2012) have  
115 horizontal resolutions between 1° to 2.5° (~ 100 – 250 km). Los Angeles' complex coastlines  
116 and topographical features show variation on much smaller scales and play a dominant role in  
117 shaping regional-scale processes, including orographic precipitation, land-sea breezes and valley  
118 circulations. Additionally, local topography introduces large spatial gradients in surface and  
119 near-surface air temperature, which influence PET. Such regional-scale processes have been  
120 shown to be critical in understanding climate variability in California (Cayan, 1996; Conil and  
121 Hall, 2006; Hughes et al. 2007). Thus, current GCM resolution is far too low to understand  
122 surface hydrology and climate at scales relevant for adaptation and water resources planning.

123

124 Dynamical-downscaling has been used to develop high-resolution regional climate data from  
125 relatively coarse-resolution GCM output, including in California (Leung et al. 2003; Leung et al.  
126 2004; Kanamitsu and Kanamaru 2007; Caldwell et al. 2009; Qian et al. 2010; Pan et al. 2011;  
127 Pierce et al. 2012) and other Mediterranean-type climate regions (Flaounas et al. 2012; Barrera-  
128 Escoda et al. 2013; Ratnam et al. 2013). The dynamical downscaling studies over California,  
129 along with a number of regional studies using hydrological models (Dettinger et al. 2004;

130 Vicuna et al. 2007; Young et al. 2009; Huang et al. 2012), have focused primarily on climate  
131 change impacts to hydrology in Central and Northern California, rather than the Los Angeles  
132 region.

133  
134 In this study, dynamical-downscaling simulations are performed to obtain high-resolution (2-km)  
135 climate information for the Los Angeles region. These consist of a validated baseline (1981-  
136 2000) climate simulation, and downscaling of output from five CMIP5 GCMs under  
137 Representative Concentration Pathway 8.5 (RCP8.5) for the mid-21<sup>st</sup> century period (2041-  
138 2060). Idealized temperature sensitivity experiments are also performed, in which the baseline  
139 climate simulation is perturbed by uniform air temperature increases of 2°, 4° and 6° C. These  
140 experiments reveal the hydrologic sensitivity to warming in the absence of precipitation change.  
141 This is a relevant simplification because the projected annual precipitation changes turn out to be  
142 quite small in this region (Berg et al. 2015). This study aims to assess changes to runoff and AET  
143 that result from precipitation and temperature changes in both the Los Angeles region and other  
144 Mediterranean-type climate regions. In the process, we will determine the degree to which  
145 sensitivity of AET and runoff to warming is indeed suppressed by the unique seasonality of  
146 Mediterranean-type climate.

147  
148 This study is part of a larger project that includes separate downscaling studies of the CMIP5  
149 ensemble's mid-21<sup>st</sup> century and end-of-21<sup>st</sup> century projections over the Los Angeles region for  
150 temperature (Walton et al. 2015; Sun et al. 2015a), precipitation (Berg et al. 2015), and snowfall  
151 and snowpack (Sun et al. 2015b). Together, these studies provide high-resolution information  
152 regarding future regional climate trends crucial for developing effective adaptation strategies.

153

154 This paper is organized as follows: Section 2 describes the model configuration and  
155 observational evaluation for the baseline simulation. Section 3 describes the future and idealized  
156 climate simulations. Section 4 presents the results of both the dynamical-downscaling  
157 simulations and the idealized temperature sensitivity experiments. This section is focused on the  
158 sensitivity of annual mean AET and runoff to both precipitation and temperature changes, while  
159 also placing changes within the context of internal interannual variability. Finally, section 5  
160 presents a discussion of the results, as well as a summary of findings.

161

## 162 **2. Baseline Simulation**

163

### 164 *a) Dynamical downscaling framework*

165

166 A dynamical downscaling simulation over the Los Angeles region is performed using the  
167 Weather Research and Forecasting Model version 3.2 (WRF; Skamarock et al. 2008). We nest  
168 higher resolution domains within one another (18-km, 6-km and 2-km) to reach a high enough  
169 resolution to represent the most important features of the region's complex topography and  
170 coastlines. Fig. 1a shows the three nested domains, as well as the topography at the resolution of  
171 the outermost domain. The outermost domain spans the entire state of California and the adjacent  
172 Pacific Ocean at 18-km resolution. The middle domain, at 6-km resolution, covers roughly the  
173 southern half of the state of California. Finally, the innermost domain, at 2-km resolution,  
174 focuses on the Los Angeles region (Fig. 1b). In the downscaling simulations, the Noah Land  
175 Surface Model (Chen and Dudhia 2001) is coupled to WRF to simulate land surface processes.

176 For additional information on parameterization options and WRF configuration settings used in  
177 the baseline simulation, the reader is directed to Walton et al. (2015).

178

179 Using this model configuration, we perform a twenty-year reanalysis-driven “baseline”  
180 simulation, which runs from September 1981 to August 2001. The baseline climate simulation is  
181 a dynamical downscaling of the National Centers for Environmental Prediction’s North America  
182 Regional Reanalysis (NARR; Mesinger et al. 2006). NARR is a coarse-resolution (32-km)  
183 reanalysis dataset that provides the lateral boundary conditions for the outermost nested WRF  
184 domain seen in Fig. 1a. This simulation reconstructs weather and climate and serves two  
185 purposes. First, it allows us to evaluate the model’s ability to simulate regional climate based on  
186 a comparison to observational data. Second, it serves as a climate state against which we can  
187 compare future climate simulations to measure climate change.

188

189 WRF is reinitialized each year in August, allowing us to run twenty one-year runs from  
190 September to August in parallel. This parallelization significantly reduces computational time.  
191 However, the annual model re-initialization prevents perfect water budget closure. To ensure the  
192 water budget is precisely closed, WRF data from the innermost (2-km) domain of the twenty  
193 one-year baseline simulations is used as forcing for a continuous twenty-year simulation using  
194 the offline 1-dimensional Noah Land Surface Model version 3.3 (Noah-LSM; Ek et al. 2003).  
195 The baseline Noah-LSM simulation is forced by WRF meteorological data, including near-  
196 surface air temperature, surface pressure, near-surface wind speed and direction, near-surface  
197 relative humidity, precipitation, and downward longwave and shortwave radiative fluxes at the  
198 surface. WRF output includes snapshots of 2-dimensional variables every 3 hours and 3-



199 dimensional variables every 6 hours for each grid point. Output from the offline Noah-LSM  
200 simulation forced by WRF output (hereinafter called Noah-LSM/WRF) precisely satisfies the  
201 surface water balance equation, solving the water budget closure issue presented by model re-  
202 initialization. As the focus of our study is terrestrial surface hydrology, we exclude ocean, lake,  
203 reservoir and urban grid points in our analysis.

204

205 *b) Baseline surface hydro-climate*

206

207 Fig. 2 shows spatial patterns of climatological precipitation, runoff and AET for the baseline  
208 period as simulated by Noah-LSM/WRF. The average annual precipitation received at non-urban  
209 land points during the baseline period (Fig. 2a) is 341 mm/yr, with 91% of the study domain's  
210 annual precipitation falling between the months of October and April. The coastal side of  
211 mountain areas above 1000m receive nearly 3 times the annual precipitation of low-elevation  
212 coastal areas due to orographic precipitation effects. The coastal areas experience greater than  
213 200mm more precipitation than the inland desert region, as moisture is wrung out of air passing  
214 over the mountain ranges toward the inland desert.

215

216 Figs. 2b and 2c present the partitioning of precipitation for the baseline Noah-LSM/WRF  
217 simulation into runoff and AET, respectively. In this semi-arid domain, 81% of annual  
218 precipitation falling on non-urban land surfaces is returned to the atmosphere through AET, on  
219 average. The ratio of runoff to precipitation is highest in coastal areas above 1000m, where  
220 runoff accounts for 41% of average incoming annual precipitation.

221

222 The annual cycle of the water balance for the baseline period is shown in Fig. 3 for two  
223 representative points in our study domain: a high-elevation mountain location (Fig. 3a) and an  
224 inland desert location (Fig. 3b). These two locations are shown in Fig. 1b by blue and red circles.  
225 The region's climate is characterized by drastic seasonal precipitation variations (especially at  
226 the high elevations) and modest seasonal transitions in temperature. In the case of the mountain  
227 location, precipitation (blue) peaks in February, and early spring snowmelt leads to maxima in  
228 both soil moisture (red) and runoff (cyan) in March. Increasing PET (black) in the late spring and  
229 early summer coincides with moist springtime soils (red), so AET (green) increases in the  
230 summer months until the soil moisture is depleted. This creates a July peak in AET. The out-of-  
231 phase relationship in the annual cycles of precipitation and PET sets up a unique response to  
232 temperature changes that will be explored later in this paper. At the desert location, annual  
233 precipitation is low, and AET is roughly equal to precipitation, accounting for over 98% of  
234 annual mean precipitation.

235

### 236 *c) Model evaluation*

237

238 Prior to analyzing surface hydrology changes, we evaluate the skill of the 2-km resolution  
239 baseline (1981-2000) simulation by comparing Noah-LSM/WRF model output to available  
240 observations.

241

242 We first briefly recapitulate an evaluation of WRF's precipitation by Berg et al. (2015). This  
243 downscaling study of precipitation changes over the Los Angeles region uses the same baseline  
244 dynamical downscaling framework as this study. Berg et al. (2015) demonstrate that this

245 modeling framework realistically simulates wet-season (December – March) precipitation in the  
246 study domain using precipitation gauges from the California Department of Water Resources’  
247 California Irrigation Management Information System (CIMIS, <http://www.cimis.water.ca.gov/>),  
248 and two gridded observational products, NOAA Climate Prediction Center Daily US UNIFIED  
249 Precipitation (CPC, <http://www.esrl.noaa.gov/psd/data/gridded/data.unified.html>) and the  
250 University of Delaware Precipitation product (Udel,  
251 [http://www.esrl.noaa.gov/psd/data/gridded/data.UDel\\_AirT\\_Precip.html](http://www.esrl.noaa.gov/psd/data/gridded/data.UDel_AirT_Precip.html)). They find a high  
252 domain-average correlation coefficient ( $r=0.82$ ) between wet-season (December – March)  
253 precipitation observed at CPC grid cells and that simulated at the nearest corresponding WRF  
254 grid cell. Overall, they find that WRF simulates monthly precipitation variations at thirteen  
255 CIMIS gauges in the study domain reasonably well, and that the WRF framework realistically  
256 simulates interannual variability in wet-season precipitation.

257

258 Next, we evaluate Noah-LSM/WRF’s simulation of streamflow, relying on the United States  
259 Geological Survey Hydro-Climatic Data Network-2009 (USGS HCDN-2009,  
260 <http://waterdata.usgs.gov/nwis/>) observational dataset. The USGS HCDN-2009 is a network of  
261 streamflow gauges across the United States identified as having: (1) natural streamflow least  
262 affected by direct human activities, (2) accurate measurement records, and (3) at least 20 years of  
263 complete and continuous discharge record through water year 2009 (Slack et al. 1993; Lins  
264 2012). We obtained daily, quality-controlled streamflow data from 3 stations for which data was  
265 available within our study domain for the baseline period. The locations of these streamflow  
266 gauges is shown in Fig. 1b by black circles. There is no runoff routing scheme in the Noah-  
267 LSM/WRF framework. To account for this, we compare the observed streamflow measurement

268 at a USGS gauge to the sum of simulated surface runoff from all grid points within a watershed  
269 upstream of the gauge. This rather primitive form of runoff routing does not account for  
270 groundwater dynamics or interactions between groundwater and surface runoff.

271

272 Fig. 4a compares monthly climatological average streamflow for USGS gauges with that  
273 simulated by Noah-LSM/WRF. Noah-LSM/WRF's simulation of the annual streamflow cycle is  
274 consistent with observations for each of the three gauges, with a correlation averaged across the  
275 gauges of  $r = 0.88$ . In addition, the points fall along the one-to-one line on the plot. Noah-  
276 LSM/WRF correctly simulates the magnitude and phasing of heightened streamflows in the  
277 months of February through May (late in the wet season), with relatively low flows the rest of  
278 the year. The root mean squared error of all data points in Fig. 4a is 0.28 cubic meters per  
279 second. These minor differences may be due to observational error or a lack of groundwater  
280 dynamics in Noah-LSM/WRF. Fig. 4b compares the annual average streamflow between each  
281 USGS gauge and the Noah-LSM/WRF simulation of runoff within the watershed for all twenty  
282 water years (September – August) of the baseline period. Correlations above  $r = 0.69$  are found  
283 at all gauges, and the gauge-average correlation is  $r = 0.77$ . Again, the points fall approximately  
284 on the one-to-one line. Overall, Figs. 4a and 4b demonstrate Noah-LSM/WRF reproduces the  
285 spatial, seasonal and interannual variations in surface runoff reasonably well.

286

287 Unfortunately, observational data networks, including FLUXNET (Balhocchi et al. 2001) and  
288 CIMIS stations, do not provide observations of AET (e.g. through measurement methods such as  
289 eddy covariance techniques, a scintillometer or lysimeter) in the study domain during the  
290 baseline period. This prevents us from comparing simulated AET to observations directly.

291 However, assuming no mean change in terrestrial water storage on annual time scales, annual  
292 mean AET must equal annual mean precipitation minus mean runoff. Because of the skill of  
293 Noah-LSM/WRF in realistically simulating interannual variability in both precipitation (Berg et  
294 al. 2015) and runoff (Fig. 4b), we can infer the model probably also realistically simulates the  
295 interannual variability in AET. Moreover, Noah-LSM/WRF's ability to accurately reproduce  
296 seasonal variations in precipitation (Berg et al. 2015) and runoff (Fig. 4a) gives us confidence in  
297 the modeling framework's ability to simulate seasonal and spatial variations in AET.

298

299 Overall, Fig. 4 and Berg et al. (2015) show that the Noah-LSM/WRF framework simulates the  
300 temporal and spatial variations of surface hydrology during the baseline period with reasonable  
301 accuracy where reliable observational data are available. Previous research also demonstrates  
302 that the WRF framework used in this study provides realistic simulations of both spatial and  
303 temporal patterns of temperature (Walton et al. 2015) and snowfall (Sun et al. 2015b). Based on  
304 this evidence, it seems likely that the model is able to realistically reproduce the temporal and  
305 spatial variations in AET and runoff across the domain, at locations where observations are not  
306 available.

307

### 308 **3. Future Simulation**

309 Using the same WRF configuration as the baseline climate simulation, we perform a second  
310 group of climate simulations designed to simulate a range of future regional climate states  
311 corresponding to the mid-21<sup>st</sup> century. By looking at differences between the future and baseline  
312 periods, mid-century changes to surface hydrology relative to the late 20<sup>th</sup> century can be  
313 quantified and evaluated. To produce boundary conditions for future simulations, we employ a

314 previously used method (Schar et al. 1996; Hara et al. 2008; Kawase et al. 2009; Rasmussen et  
315 al. 2011), in which future climate is estimated by adding a perturbation reflective of the mean  
316 climate change to reanalysis data. We apply this technique to output from five CMIP5 global  
317 climate models (CCSM4, CNRM-CM5, GFDL-CM3, MIROC-ESM-CHEM and MPI-ESM-LR)  
318 under the RCP8.5 emissions scenario for the mid-21<sup>st</sup> century period. More specifically, we  
319 perturb the NARR baseline boundary conditions (September 1981 - August 2001) by monthly-  
320 averaged differences between the future and baseline (2041-2060 minus 1981-2000) climate for  
321 each GCM. This perturbation method assumes no change in synoptic and interannual variability  
322 at the lateral boundaries. As a result, the frequency of future weather events is very similar to  
323 that of the baseline simulation (though we cannot exclude the possibility that regional climate  
324 dynamics might alter local weather events). Thus our analysis focuses on time scales of months  
325 to years.

326

327 Because it would be prohibitively expensive to perform full twenty-year future dynamical-  
328 downscaling simulations for each of the five GCMs, we first perform a future twenty-year  
329 simulation (September 2041 to August 2061) using climate change signals in CCSM4. Then we  
330 examine this experiment to assess whether short simulations can provide statistics robust enough  
331 to characterize the regional climate change signal of the full twenty-year simulation. Similar to  
332 the baseline simulation, this future simulation is reinitialized every August and run in parallel as  
333 twenty one-year simulations. Using Noah-LSM, we also perform a separate continuous twenty-  
334 year simulation of the dynamically downscaled output associated with CCSM4.

335

336 We find that we are able to capture to a high degree of accuracy the full 20-year runoff and AET  
337 signals by simulating only three future years of CCSM4. (We happened to choose September  
338 2058 to August 2061.) For example, averaged over non-urban land points, the 20-year and 3-year  
339 runoff signals associated with CCSM4 are -17.6 and -16.3 mm/yr, respectively. Previous  
340 analyses of this output found that the 20-year precipitation and temperature signals could also be  
341 captured with a high degree of precision by only dynamically-downscaling three future years  
342 (Berg et al. 2015; Walton et al. 2015). Thus, to conserve computational resources, we only  
343 dynamically downscale the remaining four GCMs (CNRM-CM5, GFDL-CM3, MIROC-ESM-  
344 CHEM and MPI-ESM-LR) for three years. For each of these four future simulations, WRF  
345 boundary conditions are created by adding the 20-year GCM climate change signal (2041–2060  
346 minus 1981–2000) to NARR data corresponding to September 1998 to August 2001. Though the  
347 future simulations of CNRM-CM5, GFDL-CM3, MIROC-ESM-CHEM and MPI-ESM-LR are  
348 only three years long, the climate change forcings therefore reflect that of a 20-year averaging  
349 period.

350

351 Similar to the twenty-year baseline and twenty-year CCSM4 simulations, the three-year mid-21<sup>st</sup>  
352 century simulations associated with CNRM-CM5, GFDL-CM3, MIROC-ESM-CHEM and MPI-  
353 ESM-LR are run as three one-year simulations re-initialized every August. The WRF output is  
354 then used to force a continuous three-year future climate simulation using Noah-LSM.

355

356 Given projections for little to no ensemble-mean precipitation change in our study domain  
357 (discussed in section 4a and Berg et al. 2015), it is useful and relevant to study the hydrologic  
358 response to warming in isolation from precipitation changes. Thus, we perform three idealized

359 twenty-year simulations with Noah-LSM designed to isolate the imprint of warming on runoff  
360 and AET. The idealized simulations are identical to the twenty-year Noah-LSM baseline (1981-  
361 2000) simulation forced by WRF data, except with a spatially uniform 2-meter air temperature  
362 increase of 2 °C, 4 °C and 6 °C at every time step. All other climatic variables are unchanged  
363 from baseline values. The idealized simulations allow us to examine the sensitivity of surface  
364 hydrology in the Los Angeles region to a range of likely temperature changes (Walton et al.  
365 2015). Increases in near-surface air temperature can affect runoff characteristics by altering the  
366 form of precipitation, AET rate and snowmelt timing. We label the results from the idealized  
367 simulations as baseline, T2, T4 and T6.

368

## 369 **4. Results**

370

371 In this section, we present results from both Noah-LSM/WRF dynamical-downscaling of GCM  
372 output and the idealized simulations.

373

### 374 *a) Small precipitation changes*

375

376 Fig. 5 (first row) shows annual mean precipitation changes for five GCMs as simulated by Noah-  
377 LSM/WRF. The precipitation projections show some intermodel spread, particularly with regard  
378 to the sign of the change. The ensemble-mean precipitation change for non-urban land surfaces  
379 across the five GCMs is -6.6 mm/yr, a minute change reflective of a cancellation between  
380 moistening (CNRM-CM5 and MPI-ESM-LR) and drying (CCSM4, GFDL-CM3 and MIROC-



381 ESM-CHEM) models. CNRM-CM5 and GFDL-CM3 project the largest precipitation changes,  
382 with changes of +51 and -39 mm/yr averaged over non-urban land surfaces, respectively.  
383  
384 These signals in precipitation changes are modest compared to the region's interannual  
385 variability. The standard deviation of baseline (1981-2000) precipitation averaged over non-  
386 urban land surfaces as simulated by Noah-LSM/WRF is 153 mm/yr, roughly 40% of the  
387 climatological mean and reflective of the region's significant interannual hydroclimate  
388 variability. Thus the downscaled change in average precipitation over non-urban land surfaces as  
389 projected by even the most extreme model (CNRM-CM5) is only about a third of the baseline  
390 interannual variability. Berg et al. (2015) further explore the region's precipitation changes, and  
391 conclude that the most likely result is a small change in mean precipitation compared to natural  
392 variability, with the sign of the change being uncertain. Berg et al. (2015) also extend the  
393 analysis to include the full CMIP5 GCM ensemble through statistical techniques. However, their  
394 results are very similar to those obtained from dynamically downscaling only these five GCMs.

395

396 *b) Runoff, AET and PET changes*

397

398 Annual mean runoff changes for the five GCMs are shown in Fig. 5 (second row). For each  
399 GCM, the runoff change mirrors the precipitation change in both sign and magnitude. Fig. 6  
400 corroborates this. The spatial patterns of precipitation change and runoff change are tightly  
401 correlated for all models, with a model-average spatial correlation coefficient of  $r = 0.88$ . For all  
402 five future simulations, the sign of the change in annual runoff is the same as the sign of the  
403 change in annual precipitation for over 98% of non-urban land grid points in the study domain.

404 Discrepancies are greatest over the desert, where a positive precipitation change may lead to a  
405 slightly negative runoff change due to enhanced AET (e.g. MIROC-ESM-CHEM). Overall, any  
406 precipitation change appears to control the runoff change. Because the precipitation changes are  
407 modest, so are the runoff change signals. For CNRM-CM5, the model with the strongest  
408 moistening, the average runoff signal over non-urban land surfaces is 34 mm/yr. The average  
409 runoff signal over non-urban land surfaces for the driest model, GFDL-CM3, is -21 mm/yr. Both  
410 values are small compared to the standard deviation of runoff in the baseline period (103 mm/yr).

411

412 We now turn to changes in PET and AET. As expected from the relationship between  
413 temperature and saturation vapor pressure, each future simulation projects a domain-wide  
414 increase in PET for all non-urban land surfaces (not shown), with an ensemble-mean change of  
415 186 mm/yr averaged over non-urban land areas. PET increases are highest above 1000m, where  
416 decreases in future snow cover and albedo during winter lead to increased absorption of  
417 downward radiation, providing more energy for PET. Annual mean AET changes are shown in  
418 Fig. 5 (third row). Despite domain-wide PET increases, AET rates are severely limited by  
419 surface water availability. In fact, for the 5 dynamically downscaled GCMs, the sign of model's  
420 precipitation change is the main determinant of the model's AET change. The partitioning of the  
421 precipitation change into a runoff change or AET change is largely determined by baseline  
422 partitioning of precipitation into runoff and AET (Fig. 2.). However, the relationship between the  
423 precipitation change and AET change is not as strong as the relationship between the  
424 precipitation change and runoff change (model-average spatial correlation coefficient of  $r = 0.61$   
425 vs.  $r = 0.88$ ).

426

427 *c) Idealized simulations: Limited influence of warming on AET*

428

429 It is noteworthy that the annual mean change in AET for each of the five dynamically-  
430 downscaled GCMs is small and precipitation-determined, even though there is significant near-  
431 surface warming. One would expect warmer surface air temperatures and increased downward  
432 longwave radiation to enhance AET throughout the domain at least somewhat. We turn to the  
433 idealized simulations to quantify the sensitivity of runoff and AET to warming in the absence of  
434 a precipitation change. By looking at differences between the idealized simulations and the  
435 baseline (1981-2000) simulation, we examine the direct influence of changing temperatures on  
436 annual mean AET and runoff.

437

438 Fig. 7. shows the change in annual 2-meter air temperature (first row) and annual AET (second  
439 row) for each of the idealized simulations: T2, T4 and T6. Due to a nearly negligible change in  
440 infiltration, the surface water balance equation constrains the runoff change for each simulation  
441 to be almost identical in magnitude to the AET change, with an opposite sign. For even the most  
442 extreme warming case (T6), the domain-average AET change over non-urban land surfaces (5.01  
443 mm/yr) pales in comparison to both the baseline mean (232 mm/yr) and interannual variability  
444 (56 mm/yr). Runoff changes are similarly miniscule. The absolute change in domain-average  
445 evaporative fraction of precipitation (E/P) increases by 0.6% from the baseline simulation to T6  
446 scenario, a tiny amount. The AET changes (second row) appear to have some spatial structure, in  
447 that the strongest AET increases are at high elevations (see topography in Fig. 1b) as well as at  
448 locations with high AET in the baseline (Fig. 2c). However, even for a mountain location where  
449 the AET signal is stronger (like the location referenced in Fig. 3a), annual AET in the T6

450 scenario increases by 11 mm/yr, a mere 2% relative increase. Without a precipitation change,  
451 surface air temperatures would have to increase significantly more than 6° C to have a substantial  
452 impact on annual AET and runoff.

453

454 The insensitivity of surface hydrology to warming is explored further in Fig. 8, which shows the  
455 average annual cycles of PET and AET over non-urban land surfaces for the baseline (1981-  
456 2000) simulation (blue), T2 (yellow), T4 (red) and T6 (black). In Fig. 8a, PET increases  
457 significantly in all idealized simulations following the monthly temperature distribution.

458 Domain-average annual PET increases by 5%, 10% and 15% for T2, T4 and T6, respectively.

459

460 In contrast, AET (Fig. 8b) remains largely unchanged in all three idealized cases. This is an  
461 artifact of Southern California's Mediterranean climate (discussed in section 1), in which the  
462 annual cycles of precipitation and soil moisture are out of phase with that of PET. In the case of  
463 T2, T4 and T6, PET increases are strongest during the months of April to October (Fig. 8a), yet  
464 soil moisture is relatively low from July to January (in both the baseline and idealized  
465 simulations) due to the seasonality of precipitation. As a result, only the months of April through  
466 June in the idealized scenarios have both significantly enhanced PET and relatively moist soils.  
467 For the most extreme warming scenario (T6), this overlap of enhanced PET and soil moisture  
468 availability leads to monthly AET increases of 7.8%, 6.5% and 5% for April, May and June,  
469 respectively (Fig. 8b). The April to June AET change then accelerates the soil moisture decrease  
470 that occurs in the baseline simulation from May to July. This exhausts nearly the same amount of  
471 soil moisture as in the baseline, but earlier in the season, with little effect on annual mean runoff.  
472 The remaining months of July through March have either limited soil moisture or relatively low

473 PET, prohibiting increases in annual total AET. Thus annual mean runoff and AET are largely  
474 insensitive to warming. One could imagine a very different situation if the study domain received  
475 significant summer rainfall, which would cause elevated soil moisture values at the same time as  
476 the peak in the annual PET cycle. In this case, warming could lead to enhanced AET and  
477 decreased annual mean runoff.

478

479 This insensitivity of annual mean runoff and AET to future temperature changes in Southern  
480 California is consistent with other studies over Northern California. Risbey and Entekhabi (1996)  
481 found annual mean streamflow in the Sacramento River to be nearly insensitive to temperature  
482 changes, but very sensitive to precipitation changes. Dettinger et al. (2004) found similar results  
483 in the Merced, Carson and American river basins of California. Together, the dynamically-  
484 downscaled GCMs and idealized simulations suggest both annual mean runoff and AET in the  
485 Los Angeles region are almost insensitive to warming, but highly sensitive to changes in annual  
486 mean precipitation.

487

## 488 **5. Summary and conclusions**

489

490 Although it has been well documented that climate change is likely to have profound impacts on  
491 the hydrology of the Western United States, few studies have examined the sensitivity of surface  
492 hydrology in the Los Angeles region to climate change. Without such analysis, the scientific  
493 foundation for informed adaptation strategies at the local and regional scale is missing. This  
494 study aims to close this knowledge gap by exploring sensitivities of both annual runoff and AET  
495 to regional precipitation and temperature changes.

496  
497  
498  
499  
500  
501  
502  
503  
504  
505  
506  
507  
508  
509  
510  
511  
512  
513  
514  
515  
516  
517

This study uses dynamical-downscaling techniques to examine mid-21<sup>st</sup> century changes to surface hydrology over the Los Angeles region under RCP8.5 for five CMIP5 GCMs: CCSM4, CNRM-CM5, GFDL-CM3, MIROC-ESM-CHEM and MPI-ESM-LR. Any change in annual precipitation is mirrored by a similar, though weaker, change in runoff. However, the average annual precipitation change over non-urban land surfaces for each GCM is small compared to their range of baseline interannual variability. Despite the warming projected by the dynamically-downscaled GCMs in this study, annual mean runoff and AET signals are also found to be well within their range of baseline interannual variability.

Given the small precipitation change, this study includes a series temperature sensitivity experiments to shed light on the hydrologic insensitivity to warming. Three idealized simulations are performed in which the baseline climate is perturbed by uniform near-surface air temperature increases of 2°, 4° and 6° C. Significant increases in annual mean PET occur with increasing temperatures, with strongest increases in the warm months. Despite significantly enhanced April to October PET in the idealized warming scenarios, available soil moisture confines AET increases to the months of April through June. Small springtime AET increases accelerate soil moisture drying, but exhaust nearly the same amount of moisture, leading to miniscule changes in annual mean runoff and AET for all idealized scenarios. This is an artifact of the out-of-phase relationship between the annual precipitation and soil moisture cycles and annual PET cycle in Mediterranean-type climate zones like the Los Angeles region.

518 The finding that annual mean runoff is nearly insensitive to temperature increases in the Los  
519 Angeles region may have implications for other Mediterranean climate regions. Surface  
520 hydrology in other Mediterranean climate zones, including most lands around the Mediterranean  
521 Sea, Western and Southern Australia, and Chile, is similar to that of the Los Angeles region, and  
522 would likely respond in a similar manner to warming. Previous studies of warming impacts to  
523 surface hydrology in Mediterranean-type climates outside California have indeed shown similar  
524 results. Chiew et al. (1995) applied a range of plausible temperature and precipitation changes to  
525 a rainfall-runoff model to study the sensitivity of runoff and soil moisture in Australian  
526 catchments to potential changes in climate. They found that compared to precipitation,  
527 temperature increases alone have negligible impacts on runoff and soil moisture. New (2002)  
528 examined the sensitivity of runoff in four mountainous catchments in the southwestern Cape of  
529 South Africa to a range of possible future climate changes, and found that streamflow in all  
530 catchments is more responsive to precipitation changes than PET changes.

531

532 One potential limitation of this study is that the modeling framework does not take into  
533 consideration the physiological effects of increased atmospheric carbon dioxide concentrations  
534 on plant stomatal resistance (i.e. CO<sub>2</sub> fertilization). Increases in atmospheric carbon dioxide  
535 concentrations enhance the leaf's internal carbon dioxide absorption rate. This gives plants the  
536 flexibility to increase their stomatal resistance to conserve water. CO<sub>2</sub> fertilization generally  
537 results in a decrease of canopy transpiration and therefore affects the water balance (Betts et al.  
538 2007). In our simulations, the CO<sub>2</sub> fertilization effect would reduce AET sensitivity to  
539 temperature increases still further by reducing AET. Therefore, if this study had included CO<sub>2</sub>

540 fertilization effects, the result that annual mean AET and runoff are nearly insensitive to  
541 temperature increases would hardly change.

542

543 This study diagnoses the sensitivity of the Los Angeles region's surface hydrology to both  
544 precipitation and temperature changes. Together, the dynamically-downscaled GCMs and  
545 idealized simulations suggest both annual mean runoff and actual evapotranspiration in the Los  
546 Angeles region are almost insensitive to warming, but are instead controlled by possible changes  
547 in annual mean precipitation. Surface hydrology in other Mediterranean climate regions will  
548 likely behave similarly. This result greatly mitigates a potential vulnerability of water resources  
549 to a changing climate in an important semi-arid region of the world. It also reveals that a regional  
550 climate change adaptation strategy relying on local water resources is a viable one.

551

552

553

554

555

556

557

558

559

## 560 **Acknowledgments**

561 Support for this work was provided by the City of Los Angeles and the US Department of  
562 Energy as part of the American Recovery and Reinvestment Act of 2009. Additional funding  
563 was provided by the National Science Foundation (Grant #EF-1065863, "Collaborative  
564 Research: Do Microenvironments Govern Macroecology?").



565 **References**

- 566 Adam, J.C., A.F. Hamlet, D.P. Lettenmaier, 2009: Implications of global climate change for  
567 snowmelt hydrology in the twenty-first century. *Hydrol. Process.* 23, 962–972.  
568
- 569 Baldocchi, D., et al., 2001: FLUXNET: A new tool to study the temporal and spatial variability  
570 of ecosystem-scale carbon dioxide, water vapor, and energy flux densities. *Bull. Am. Meteorol.*  
571 *Soc.*, 82(11), 2415–2434.  
572
- 573 Barnett, T.P., D.W. Pierce, H.G. Hidalgo, C.B. Benjamin, D. Santer, T. Das, G. Bala, A.W.  
574 Wood, T. Nozawa, A.A. Mirin, D.R. Cayan, and M.D. Dettinger, 2008: Human-induced changes  
575 in the hydrology of the Western United States. *Science*, 319, 1080–1083.  
576
- 577 Barrera-Escoda, A., M. Gonçalves, D. Guerreiro, J. Cunillera, J.M. Baldasano, 2013: Projections  
578 of temperature and precipitation extremes in the North Western Mediterranean Basin by  
579 dynamical downscaling of climate scenarios at high resolution (1971–2050). *Climatic Change* pp  
580 1–16. doi:10.1007/s10584-013-1027-6.  
581
- 582 Bates, B.C., Z.W. Kundzewics, S. Wu, and J.P. Palutikof, 2008: *Climate Change and Water*.  
583 Technical Paper of the Intergovernmental Panel on Climate Change. IPCC Secretariat, Geneva,  
584 Switzerland, 210 pp.  
585
- 586 Berg, N., A. Hall, F. Sun, S. Capps, D. Walton, B. Langenbrunner, and J. Neelin, 2015: Twenty-  
587 First-Century Precipitation Changes over the Los Angeles Region. *J. Climate*, 28, 401-421.  
588 doi:10.1175/JCLI-D-14-00316.1  
589
- 590 Betts, R.A., O. Boucher, M. Collins, P.M Cox, P.D. Falloon, N. Gedney, D.L. Hemming, C.  
591 Huntingford, C.D. Jones, D.M.H. Sexton, and M. Webb, 2007: Projected increase in continental  
592 runoff due to plant responses to increasing carbon dioxide. *Nature*, 448, 1037-1042.  
593
- 594 Blanco, H. P., J. Newell, L. Stott, M. Alberti, 2012: *Water Supply Scarcity in Southern*  
595 *California: Assessing Water District Level Strategies*. Los Angeles, CA: Center for Sustainable  
596 Cities, Price School of Public Policy, University of Southern California.  
597 <http://sustainablecities.usc.edu/research/Chapter%203.%20LADWP%2012%2019%20p.pdf>  
598
- 599 Caldwell, P., H.N.S. Chin, D.C. Bader, and G. Bala, 2009: Evaluation of a WRF dynamical  
600 downscaling simulation over California. *Climatic Change*, 95, 499-521.  
601
- 602 Cayan, D.R., 1996: Interannual climate variability and snowpack in the western United States.  
603 *Journal of Climate*, 9, 928-948.  
604
- 605 Chiew, F.H.S., P.H. Whetton, T.A. McMahon, and A.B. Pittock, 1995: Simulation of the impacts  
606 of climate change on runoff and soil moisture in Australian catchments. *Journal of Hydrology*,  
607 167, 121-147.  
608
- 609 Chen, F., and J. Dudhia, 2001: Coupling an advanced land surface-hydrology model with the

610 Penn State-NCAR MM5 modeling system. Part I: Model implementation and sensitivity. *Mon.*  
611 *Wea. Rev.*, 129, 569-585. doi:10.1175/1520-0493(2001)129,0569: CAALSH.2.0.CO;2.  
612  
613 City of Camarillo, 2010: *Urban Water Management Plan 2010*. Available at  
614 [http://www.water.ca.gov/urbanwatermanagement/2010uwmps/Camarillo,%20City%20of/2010%](http://www.water.ca.gov/urbanwatermanagement/2010uwmps/Camarillo,%20City%20of/2010%20UWMP%20Final%20Draft.pdf)  
615 [20UWMP%20Final%20Draft.pdf](http://www.water.ca.gov/urbanwatermanagement/2010uwmps/Camarillo,%20City%20of/2010%20UWMP%20Final%20Draft.pdf)  
616  
617 Conil, S. and A. Hall, 2006: Local regimes of atmospheric variability: A case study of Southern  
618 California. *Journal of Climate*, 19, 4308-4325.  
619  
620 Cowling R.M., P.W. Rundel, B.B. Lamont, M.K. Arroyo, M. Arianoutsou, 1996: Plant diversity  
621 in Mediterranean-climate regions. *Trends in Ecology and Evolution*, 11: 362–366  
622  
623 Cowling, R. M., F. Ojeda, B. B. Lamont, P. W. Rundel, and R. Lechmere-Oertel, 2005: Rainfall  
624 reliability a neglected factor in explaining convergence and divergence of plant traits in fire-  
625 prone mediterranean-climate ecosystems. *Glob. Ecol. Biogeogr.* 14: 509–519.  
626  
627 Dettinger, M.D., D.R. Cayan, M.K. Meyer, A.E. Jeton, 2004: Simulated hydrologic responses to  
628 climate variations and changes in the Merced, Carson, and American river basins, Sierra Nevada,  
629 California, 1900–2099. *Clim. Change*, 62, 283–317.  
630  
631 Ek, M. B., K. E. Mitchell, Y. Lin, E. Rogers, P. Grunmann, V. Koren, G. Gayno, J.D.  
632 Tarpley, 2003: Implementation of Noah land surface model advances in the National Centers  
633 for Environmental Prediction operational mesoscale Eta model. *Journal of*  
634 *Geophysical Research*, 108 (D22), 8851.  
635  
636  
637 Flaounas, E., P. Drobinski, M. Vrac, S. Bastin, C. LebeaupinBrossier, M. Stefanon, M. Borga,  
638 and J. Calvet, 2012: Precipitation and temperature space–time variability and extremes in the  
639 Mediterranean region: Evaluation of dynamical and statistical downscaling methods. *Climate*  
640 *Dynamics*, 40: 2687–2705. DOI: 10.1007/s00382-012-1558-y.  
641  
642 Giorgi, F., and L. O. Mearns, 1991: Approaches to regional climate change simulation: A  
643 review. *Rev. Geophys.*, 29, 191–216.  
644  
645 Hamlet, A., P. Mote, M. Clark, and D. Lettenmaier, 2005: Effects of temperature and  
646 precipitation variability on snowpack trends in the western United States. *J. Climate*, 18, 4545–  
647 4560.  
648  
649 Hara, M., T. Yoshikane, H. Kawase, and F. Kimura, 2008: Estimation of the impact of global  
650 warming on snow depth in Japan by the pseudo-global warming method. *Hydrol. Res. Lett.*, 2,  
651 61–64.  
652  
653 Huang, G., Kadir, T. and F. Chung, 2012: Hydrological response to climate warming: The Upper  
654 Feather River Watershed, *Journal of Hydrology*, Volumes 426–427, 138-150.  
655

656 Hughes M., A. Hall, R.G. Fovell, 2007: Dynamical controls on the diurnal cycle of temperature  
657 in complex topography. *Climate Dynamics*, 29, 277-292.  
658

659 IPCC [Intergovernmental Panel on Climate Change]. 2014. *Climate Change 2014: Impacts,*  
660 *adaptation and vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working*  
661 *Group II to the Fifth Assessment Report of the Intergovernment Panel on Climate Change.* Field  
662 C. B., V.R. Barros, D.J. Dokken, K.J. Mach, M.D. Mastrandrea, T.E. Bilir, M. Chatterjee, K.L.  
663 Ebi, Y.O. Estrada, R.C. Genova, B. Girma, E.S. Kissel, A.N. Levy, S. MacCracken, P.R.  
664 Mastrandrea, and L.L. White (eds.) Cambridge University Press, Cambridge, United Kingdom  
665 and New York, NY, USA, 1132 pp.  
666

667 Kanamitsu, M., and H. Kanamaru, 2007: Fifty-seven-year California reanalysis downscaling at  
668 10 km (CaRD10). Part I: system detail and validation with observations. *Journal of Climate*, 20  
669 (22), 5553–5571.  
670

671 Kapnick, S., and A. Hall, 2010: Observed climate-snowpack relationships in California and their  
672 implications for the future. *J. Clim.* 23: 3446-3456, DOI:10.1175/2010JCLI203.1  
673

674 Kawase, H., T. Yoshikane, M. Hara, F. Kimura, T. Yasunari, B. Ailikun, H. Ueda, and T. Inoue,  
675 2009: Intermodel variability of future changes in the Baiu rainband estimated by the pseudo  
676 global warming downscaling method. *J. Geophys. Res.*, 114, D24110,  
677 doi:10.1029/2009JD011803.  
678

679 Kottke, M., Grieser, J., Beck, C., Rudolf, B., Rubel, F., 2006. World Map of the Köppen–  
680 Geiger climate classification updated. *Meteorol. Z.* 15, 259–263. doi:10.1127/ 0941-  
681 2948/2006/0130.  
682

683 Leung, L.R., Y. Qian, X. Bian, 2003: Hydroclimate of the western United States based on  
684 observations and regional climate simulations of 1981-2000. Part I: seasonal statistics. *Journal of*  
685 *Climate*, 16, 1892-1911.  
686

687 Leung L.R., Y. Qian, X. Bian, W.M. Washington, J. Han, J. Roads, 2004: Mid-century ensemble  
688 regional climate change scenarios for the western United States. *Climatic Change* 62, 75– 113.  
689

690 Lins, H.F, 2012: USGS Hydro-Climatic Data Network 2009 (HCDN-2009). U.S. Geological  
691 Survey Fact Sheet. 2012-3047. <http://pubs.usgs.gov/fs/2012/3047>.  
692

693 Long Beach Water Department, 2010: *Urban Water Management Plan*. Available at  
694 [http://www.water.ca.gov/urbanwatermanagement/2010uwmps/Long%20Beach%20Water%20De](http://www.water.ca.gov/urbanwatermanagement/2010uwmps/Long%20Beach%20Water%20Department/2010%20UWMP%20-%20Revised%20110915%20-%20FINAL.pdf)  
695 [partment/2010%20UWMP%20-%20Revised%20110915%20-%20FINAL.pdf](http://www.water.ca.gov/urbanwatermanagement/2010uwmps/Long%20Beach%20Water%20Department/2010%20UWMP%20-%20Revised%20110915%20-%20FINAL.pdf)  
696

697 Masiokas, M., R. Villalba, B. Luckman, C. Le Quesne and J.C. Aravena, 2006: Snowpack  
698 variations in the Central Andes of Argentina and Chile, 1951–2005. Large-scale atmospheric  
699 influences and implications for water resources in the region. *J. Climate* 19, 6334–6352.  
700

701 Maurer, E.P, 2007: Uncertainty in hydrologic impacts of climate change in the Sierra Nevada,  
702 California under two emissions scenarios *Clim. Change*, 82 (3–4), 309–325.  
703  
704 Mesinger, F., G. DiMego, E. Kalnay, K. Mitchell, P.C. Shafran, W. Ebisuzaki, and W. Shi, 2006:  
705 North American regional reanalysis. *Bull. Amer. Meteor. Soc.*, 87(3), 343–360.  
706  
707 Myers, N., R. A. Mittermeier, C. G. Mittermeier, G. A. B. da Fonseca, and J. Kent, 2000:  
708 Biodiversity hot spots for conservation priorities. *Nature* 403:853–858.  
709  
710 New, M., 2002: Climate change and water resources in the southwestern Cape, South Africa.  
711 *South African Journal of Science*, 98: 369–376.  
712  
713 Pan, L.-L., S.-H. Chen, D. Cayan, M.-Y. Lin, Q. Hart, M.-H. Zhang, Y. Liu, J. Wang, 2011:  
714 Influences of climate change on California and Nevada regions revealed by a high- resolution  
715 dynamical downscaling study. *Climate Dynamics*, 37, 2005-2020.  
716  
717 Paton, F. L., H. R. Maier, and G. C. Dandy, 2013): Relative magnitudes of sources of uncertainty  
718 in assessing climate change impacts on water supply security for the southern Adelaide water  
719 supply system, *Water Resour. Res.*, 49, 1643–1667, doi:10.1002/wrcr.20153.  
720  
721 Pierce, D.W., T. Das, D.R. Cayan, E.P. Maurer, N.L. Miller, Y. Bao, M. Kanamitsu, K.  
722 Yoshimura, M.A. Snyder, L.C. Sloan, G. Franco, and M. Tyree, 2012: Probabilistic estimates of  
723 future changes in California temperature and precipitation using statistical and dynamical  
724 downscaling. *Clim. Dyn.*,  
725  
726 Qian, Y., S.J. Ghan, L.R. Leung, 2009: Downscaling hydroclimatic changes over the Western  
727 U.S. Based on CAM subgrid scheme and WRF regional climate simulations, *International*  
728 *Journal of Climatology*, 30, 675-693.  
729  
730 Rasmussen, R. and Coauthors, 2011: High-Resolution Coupled Climate Runoff Simulations of  
731 Seasonal Snowfall over Colorado: A Process Study of Current and Warmer Climate. *J.*  
732 *Climate*, 24, 3015–3048  
733  
734 Ratnam, J.V., S. K. Behera, S. B. Ratna, C. J. de W. Rautenbach, C. Lennard, J.-J. Luo, Y.  
735 Masumoto, K. Takahashi, and T. Yamagata, 2013: Dynamical Downscaling of Austral Summer  
736 Climate Forecasts over Southern Africa Using a Regional Coupled Model. *J. Climate*, 26, 6015–  
737 6032. doi: <http://dx.doi.org/10.1175/JCLI-D-12-00645.1>  
738  
739  
740 Risbey, J.S. and D. Entekhabi, 1996: Observed Sacramento Basin streamflow response to  
741 precipitation and temperature changes and its relevance to climate impact studies *J. Hydrol.*, 184,  
742 209–223.  
743  
744 Roos, M., 1991. A trend of decreasing snowmelt runoff in northern California. In: 59th Western  
745 Snow Conference, Juneau, AK, pp. 29–36.  
746

747 Schär, C., C. Frei, D. Lüthi, and H. C. Davies, 1996: Surrogate climate-change scenarios for  
748 regional climate models. *Geophys. Res. Lett.*, 23(6), 669–672. doi:10.1029/96GL00265.  
749

750 Skamarock, W.C., Klemp J.B., Dudhia J., Gill D.O., Barker D.M., Duda M.G., Huang X-Y,  
751 Wang W., Powers J.G., 2008: A Description of the Advanced Research WRF Version 3. NCAR  
752 Technical Note, NCAR/TN-475+STR.  
753

754 Slack, J. R., A. M. Lumb, and J. M. Landwehr, 1993: Hydroclimatic data network (HCDN): A  
755 U.S. Geological Survey streamflow data set for the United States for the study of climate  
756 variation, 1874–1988, U.S. Geol. Surv. Water Resour. Invest. Rep. [CD-ROM], 93-4076.  
757

758 Sun F., D Walton, and A Hall, 2015a: A hybrid dynamical–statistical downscaling technique,  
759 part II: End-of-century warming projections predict a new climate state in the Los Angeles  
760 region. *Journal of Climate*, in press.  
761

762 Sun F., A. Hall, M. Schwartz, D. Walton and N. Berg, 2015b: 21st-century snowfall and  
763 snowpack changes over the southern California mountainous region. *Journal of*  
764 *Climate*, submitted.  
765

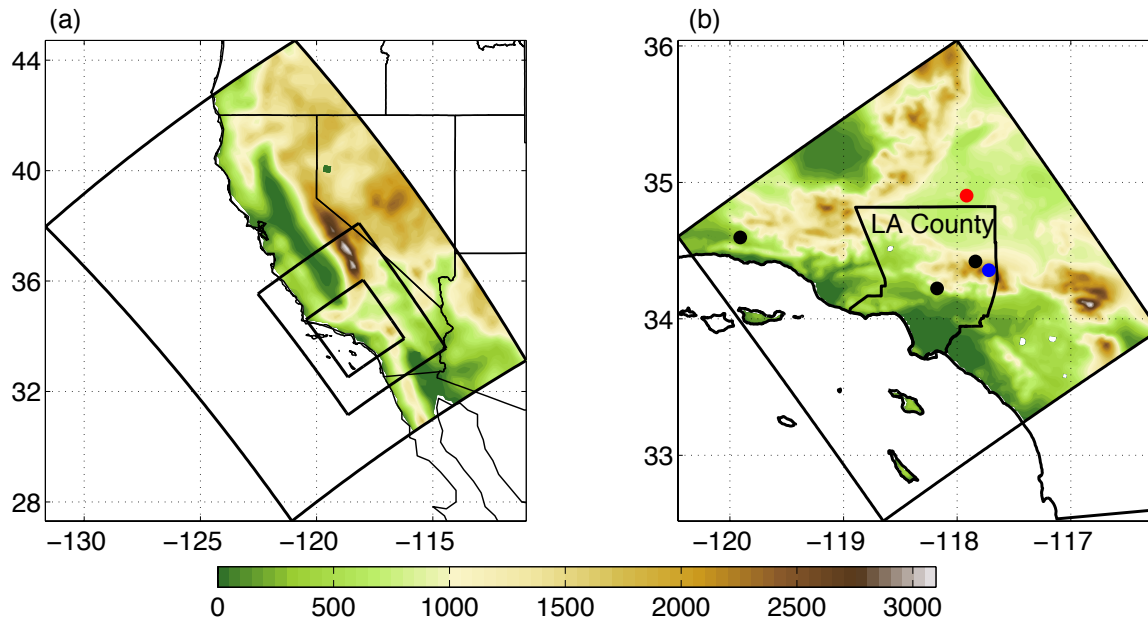
766 Taylor, K. E., R. J. Stouffer, and G. A. Meehl, 2012: An overview of CMIP5 and the experiment  
767 design. *Bull. Amer. Meteor. Soc.*, 93(4), 485–498.  
768

769 Vicuna, S., E.P. Maurer, B. Joyce, J.A. Dracup, D. Purkey, 2007: The Sensitivity of California  
770 water resources to climate change scenarios *J. Am. Water Resour. Assoc.*, 43, 482–498  
771

772 Walton D., F. Sun, A. Hall and S. Capps, 2015: A Hybrid Dynamical-Statistical Downscaling  
773 Technique, Part I: Development and Validation of the Technique. *Journal of Climate*, in press.  
774

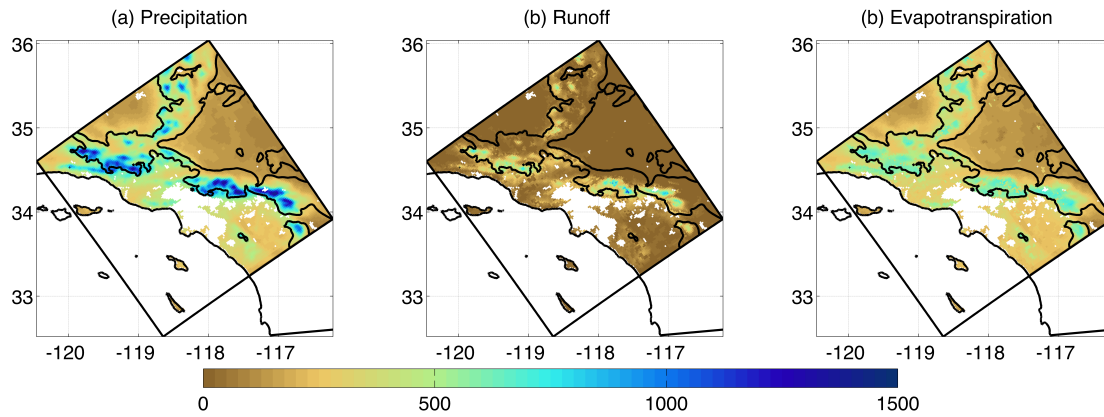
775 Young, C.A., M. Escobar, M. Fernandes, B. Joyce, M. Kiparsky, et al., 2009: Modeling the  
776 Hydrology of California's Sierra Nevada for Sub-Watershed Scale Adaptation to Climate  
777 Change. *J. Am. Water Resour. Assoc. (JAWRA)*, 45 (6), 1409-1423.  
778

779 Ziervogel, G., P. Johnston, M. Matthew and P. Mukheibir, 2010: Using climate information for  
780 supporting climate change adaptation in water resource management in South Africa. *Climatic*  
781 *Change*, 103: 537–554. DOI 10.1007/s10584-009-9771-3.  
782



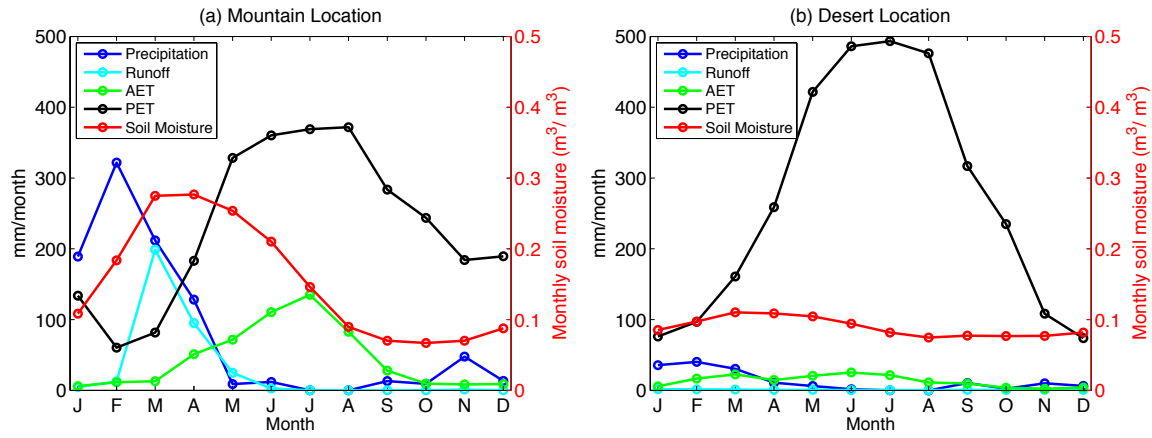
783

784 FIG. 1: a) Model setup, with three nested WRF domains at resolutions of 18, 6, and 2 km.  
 785 Topography (m) is shown at the resolution of the 18km domain in color and black lines show  
 786 boundaries for US states. (b) Topography of the innermost domain (2- km resolution) of the  
 787 regional simulation, with the border of Los Angeles County in black. In (b), black circles  
 788 indicate locations of the 3 gauges used for streamflow validation. The blue and red circles in (b)  
 789 indicate the mountain location and desert location, respectively, referenced in Fig. 3 and section  
 790 2b.



791

792 FIG. 2: Noah-LSM/WRF simulation of annual a) accumulated precipitation, b) runoff and c)  
 793 actual evapotranspiration for the baseline (1981-2000) period. Unit is mm/yr. The 1000m  
 794 topography contour is highlighted in black. Grid cells with missing values are urban or over  
 795 water surfaces.  
 796

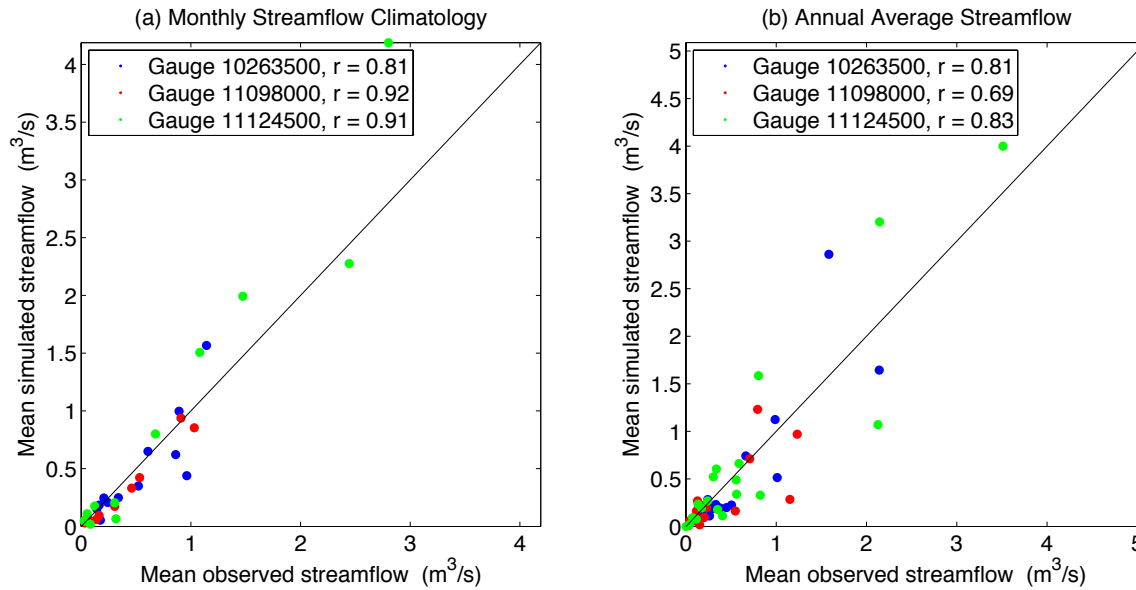


797

798  
799  
800  
801  
802  
803  
804

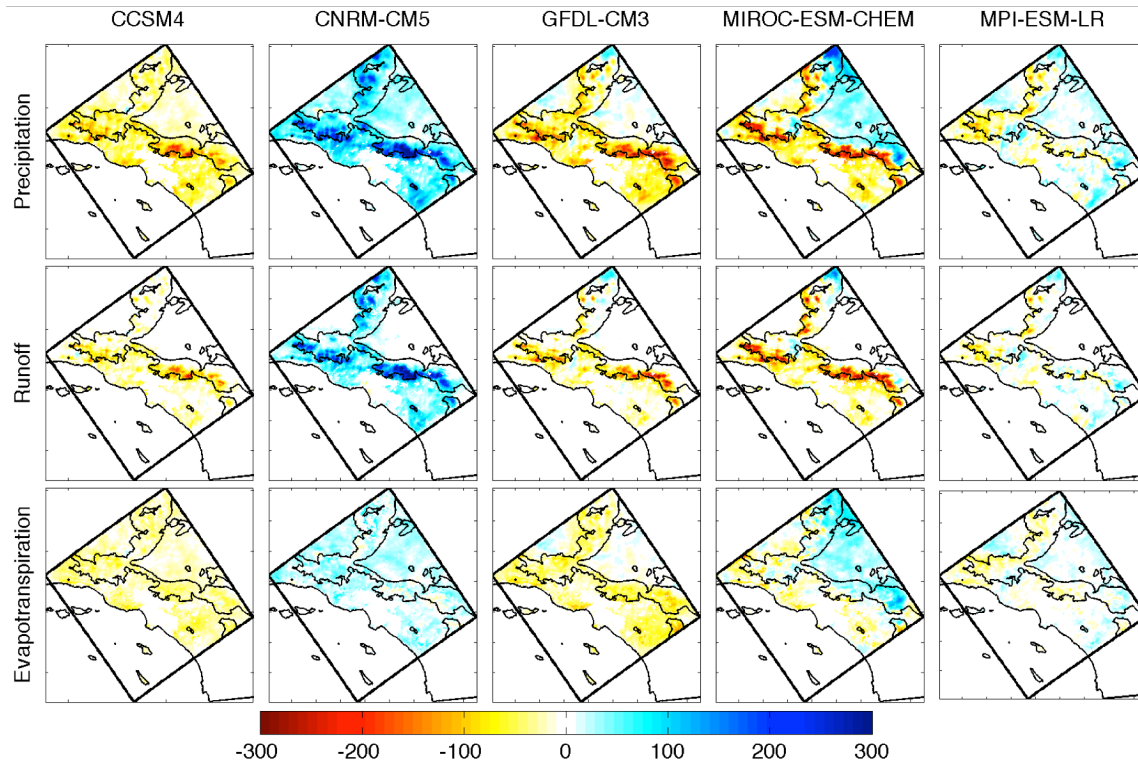
FIG. 3: Noah-LSM/WRF simulation of the mean annual cycle of the water balance at a point representative of (a) mountain locations and (b) the inland desert. Monthly accumulated values (unit: mm/month) of precipitation (blue), runoff (cyan), actual evapotranspiration (green) and potential evapotranspiration (black) are shown with respect to the left y-axis. The climatological monthly soil moisture (unit:  $m^3/m^3$ ) of the top 2m of the soil column is also shown (red) with respect to the right y-axis.





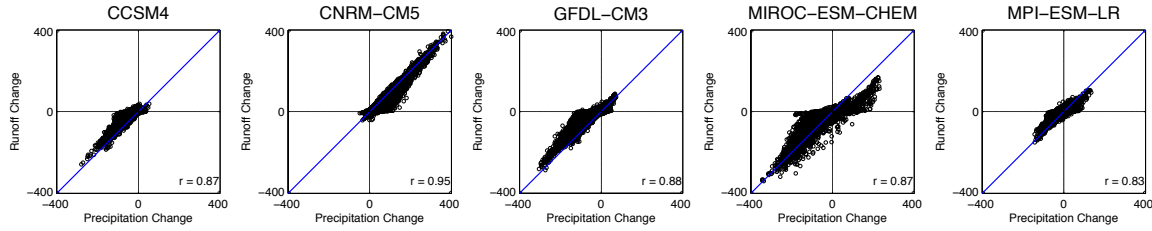
805  
 806  
 807  
 808  
 809  
 810  
 811  
 812

FIG. 4: Evaluation of Noah-LSM/WRF dynamical downscaling of runoff during the baseline period for three streamflow gauges. a) Observed vs. simulated monthly mean streamflow. b) Observed vs. simulated annual mean streamflow. Observed streamflow data is compared to simulated surface runoff aggregated upstream of the gauge within a watershed. Correlation coefficients for each gauge are also presented. The line  $y = x$  is shown in black.



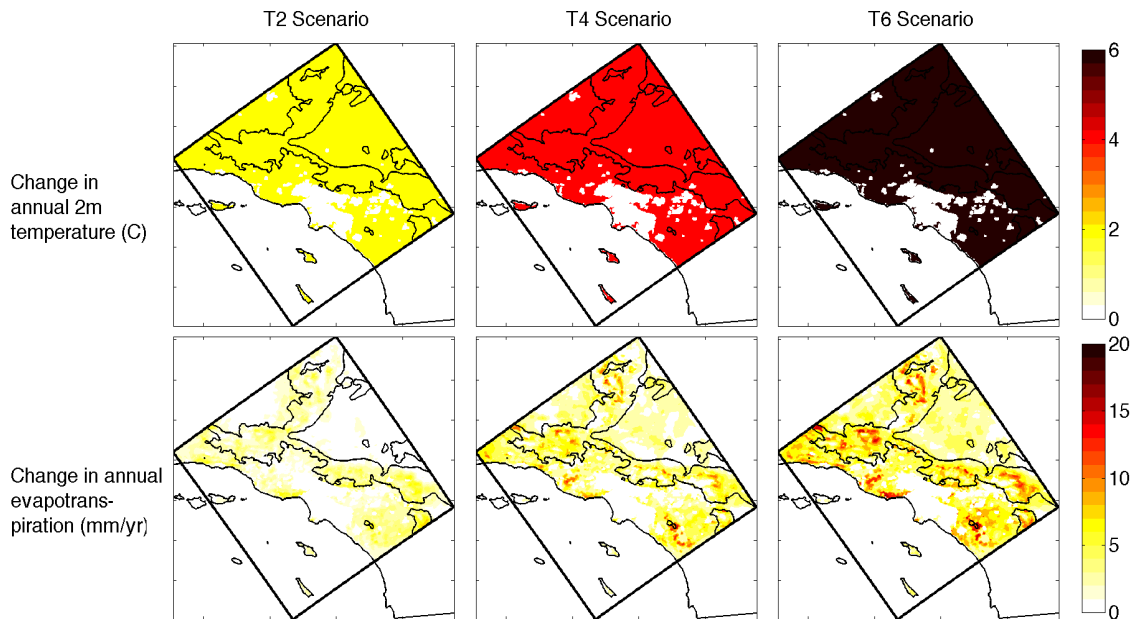
813  
814  
815  
816  
817  
818  
819  
820

FIG. 5: Noah-LSM/WRF simulation of the mid-21<sup>st</sup> century change (mm/yr) in precipitation (row 1), runoff (row 2) and actual evapotranspiration (row 3) relative to the baseline period for five GCMs under RCP8.5: CCSM4, CNRM-CM3, GFDL-CM3, MIROC-ESM-CHEM and MPI-ESM-LR. Blue shading indicates moistening, while yellow/red shading indicates drying. The 1000m topography contour is highlighted.

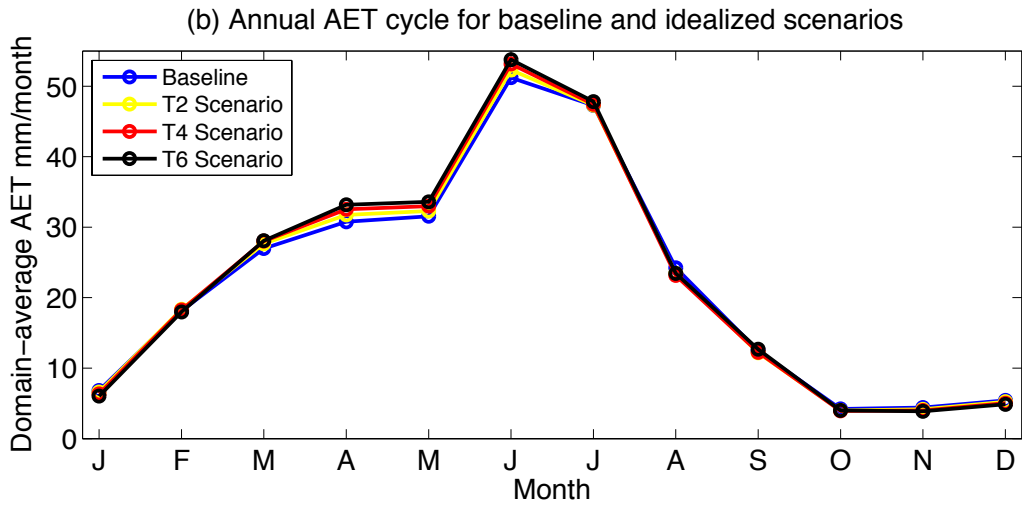
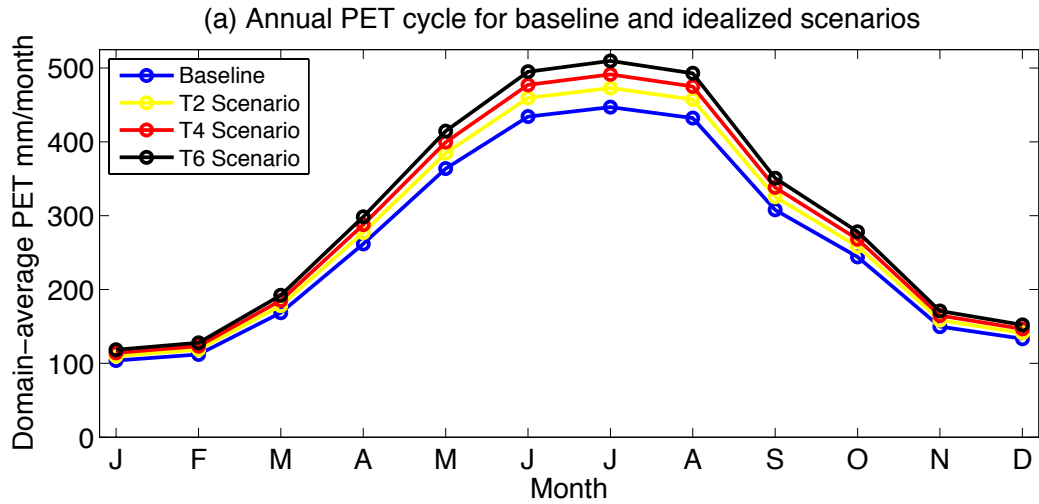


821  
822  
823  
824  
825  
826  
827  
828

FIG. 6: Scatter plot of mid-21<sup>st</sup> century change in annual precipitation (mm/yr) vs. annual runoff (mm/yr) at all non-urban land surface in the study domain when five GCMs under RCP8.5 are downscaled: CCSM4, CNRM-CM3, GFDL-CM3, MIROC-ESM-CHEM and MPI-ESM-LR. Correlation coefficients are shown in the bottom corner for each plot. The line  $y = x$  is shown in blue.



829  
 830 FIG. 7: Results from three idealized simulations in which Noah-LSM/WRF dynamically-  
 831 downscaled output for the baseline (1981-2000) period is perturbed by a uniform increase in  
 832 near-surface air temperature of 2° C (left column, T2 scenario), 4° C (center column, T4  
 833 scenario), and 6° C (right column, T6 scenario). Changes in annual near-surface air temperature  
 834 (first row, unit: °C) and actual evapotranspiration (second row, unit: mm/yr) are shown for each  
 835 idealized scenario. Precipitation is not perturbed. The 1000m topography contour is shown.  
 836



837  
 838 FIG. 8: Noah-LSM simulation of the domain-average annual cycle of (a) potential  
 839 evapotranspiration and (b) actual evapotranspiration over non-urban land surfaces for the  
 840 baseline (1981-2000) simulation (blue) and three idealized simulations in which the baseline  
 841 simulation is perturbed by a uniform increase in near-surface air temperature of 2° C (yellow, T2  
 842 scenario), 4° C (red, T4 scenario), and 6° C (black, T6 scenario). Unit: mm/month.