

Author’s response letter for “Sensitivity of future Continental United States water deficit projections to General Circulation Model, evapotranspiration estimation method, and greenhouse gas emission scenario.” by S. Chang et al.

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We appreciate the thoughtful comments from the referee #2, which have helped us to improve the original manuscript. We explain in detail how we responded to each of comments, with line numbers referring to the revised manuscript unless otherwise noted.

Referee #2

Index		Comments
1	Referee review	Lines 67-75. Although the authors have summarized some literatures on that future ET ₀ projections have been shown to depend on ET ₀ estimation methods in addition to GCMs, here, the authors appear to miss some new literatures on the impact of different combinations between methods and GCM data on projecting ET ₀ (e.g., Wang et al., 2015).
	Author’s response	We added the reference in the introduction section. After line 67 : “For example, Wang et al. (2015) used projections from the CMIP3 HADCM3 model A2 scenario and found that the physically-based Penman-Monteith equation, which uses less reliable GCM projection data (including vapor pressure and solar radiation), and the empirical temperature-based Hargreaves equation showed similar patterns but different magnitudes for future ET ₀ changes over the Hanjiang River Basin in China.”
2	Referee review	Lines 95. Given a large number of publications on future ET ₀ projection, the motivation of this study should be further explain to emphasize what new contribution it makes to the field, rather than only stated that “adds to the literature”.
	Author’s response	We revised the contribution statement to “ <i>In this study we perform a comprehensive evaluation of the relative sensitivity of future P, ET₀ and water deficit (defined here as P- ET₀) projections to choice of GCM, ET₀ method and RCP trajectory over the continental USA using CMIP5 GCM model outputs to provide new insights that will inform more robust future water resource planning efforts.</i> ”
3	Referee review	Although the authors divide the results into several paragraphs, it maybe not clear enough for reader. Therefore, it will be better to give the suitable titles for sub-sections
	Author’s response	We divided the results section into four subsections including: “ <i>3.1. Projected P, ET₀, and water deficit change in the 21st century, 3.2. Global sensitivity analysis of projected changes, 3.3. Change in annual mean water deficit projections using different ET₀ methods, and 3.4. Monte Carlo filtering.</i> ”
4	Referee review	I would prefer a shorter conclusion, this one is more like a summary. Some discussion about future research (e.g., Lines 407-413) should be moved to the discussion section. Moreover, the authors need realize that some recent literatures have done the related work on weighting the results of the ensemble of GCMs when projecting ET ₀ (e.g., Xing et al., 2014).
	Author’s response	We retitled the section from “ <i>Conclusion</i> ” to “ <i>Summary and Conclusions</i> ”, and omitted lines 370-379 from the section. In addition we added the suggested reference (Xing et al. 2014) in the section as the example of weighting the results of an ensemble of GCMs and ET methods.

5	Referee review	Figure 8 missed the scale of x-axis.
	Author's response	We replaced figure 8 to include the scale of x-axis.

Additional literature cited:

Wang, W., Xing, W. and Shao, Q.: How large are uncertainties in future projection of reference evapotranspiration through different approaches?, *J. Hydrol.*, 524, 696–700, doi:10.1016/j.jhydrol.2015.03.033, 2015.

Xing, W., Wang, W., Shao, Q., Peng, S., Yu, Z., Yong, B. and Taylor, J.: Changes of reference evapotranspiration in the Haihe River Basin: Present observations and future projection from climatic variables through multi-model ensemble, *Glob. Planet. Change*, 115, 1–15, doi:10.1016/j.gloplacha.2014.01.004, 2014.

Sensitivity of future Continental United States water deficit projections to General Circulation Model, evapotranspiration estimation method, and greenhouse gas emission scenario

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Abstract

Projecting water deficit under various possible future climate scenarios depends on the choice of General Circulation Model (GCM), reference evapotranspiration (ET_0) estimation method and Representative Concentration Pathway (RCP) trajectory. The relative contribution of each of these factors must be evaluated in order to choose an appropriate ensemble of future scenarios for water resources planning. In this study variance-based global sensitivity analysis and Monte Carlo filtering were used to evaluate the relative sensitivity of projected changes in precipitation (P), ET_0 and water deficit (defined here as $P - ET_0$) to choice of GCM, ET_0 estimation method and RCP trajectory over the continental United States (US) for two distinct future periods: 2030-2060 (future period 1) and 2070-2100 (future period 2). A total of 9 GCMs, 10 ET_0 methods and 3 RCP trajectories were used to quantify the range of future projections and estimate the relative sensitivity of future projections to each of these factors. In general, for all regions of the Continental US, changes in future precipitation are most sensitive to the choice of

27 GCM, while changes in future ET_0 are most sensitive to the choice of ET_0 estimation method.
28 For changes in future water deficit, the choice of GCM is the most influential factor in the cool
29 season (Dec – Mar) and the choice of ET_0 estimation method is most important in the warm
30 season (May – Oct) for all regions except the South East US where GCM and ET_0 have
31 approximately equal influence throughout most of the year. Although the choice of RCP
32 trajectory is generally less important than the choice of GCM or ET_0 method, the impact of RCP
33 trajectory increases in future period 2 over future period 1 for all factors. Monte Carlo filtering
34 results indicate that particular GCMs and ET_0 methods drive the projection of wetter or drier
35 future conditions much more than RCP trajectory; however the set of GCMs and ET_0 methods
36 that produce wetter or drier projections varies substantially by region. Results of this study
37 indicate that, in addition to using an ensemble of GCMs and several RCP trajectories, a range of
38 regionally-relevant ET_0 estimation methods should be used to develop a robust range of future
39 conditions for water resource planning under climate change.

40

41 **1. Introduction**

42 Climate change will result in significant impacts on hydrologic processes. The 2014 Fifth
43 Assessment Report (AR5) of the Intergovernmental Panel on Climate Change (IPCC) reported
44 that climate change will significantly affect future precipitation (P), temperature (T) and
45 reference evapotranspiration (ET_0) and these changes will affect the quantity and quality of water
46 resources. The most recent report of the National Climate Assessment and Development
47 Advisory Committee (NCADAC, 2013) indicated that the average annual temperature in the
48 United States (US) has increased by 0.7 °C to 0.9 °C since record keeping began in 1895 and is
49 expected to continue to rise (Georgakakos et al., 2014; Walsh et al., 2014). The NCADAC report
50 also indicated that Coupled Model Intercomparison Project 5 (CMIP5) General Circulation
51 Model (GCM) precipitation projections show a consistent increase in Alaska and the far north of
52 the continental US and a consistent decrease in the far Southwest US, but that GCM projections
53 are inconsistent in the precipitation transition zone of the US continent. The uncertainty in
54 climate change projections makes actionable water resources planning difficult in many regions.
55 In order to predict changes in the hydrologic cycle, and future water supply and demand,

56 estimates of changes in P, T and ET_0 must be evaluated on a regional basis, and the uncertainty
57 of these estimates must be quantified (Ishak et al., 2010).

58 Previous research has evaluated existing and potential future spatiotemporal changes in P,
59 T and ET_0 for various regions around the globe (e.g. Chaouche et al., 2010; Chong-Hai and
60 Ying, 2012; Johnson and Sharma, 2009; Kharin et al., 2013; Maurer and Hidalgo, 2008;
61 Quintana Seguí et al., 2010; Sung et al., 2012; Thomas, 2000; Wang et al., 2013; Xu et al.,
62 2006). It is well known that future GCM projections of temperature and precipitation vary
63 significantly due to both the different radiative forcing assumptions of carbon dioxide scenarios
64 (e.g. CMIP3 Special Report on Emissions Scenarios (SRES) and CMIP5 Representative
65 Concentration Pathways (RCP trajectories)) and different GCM model physics (Hawkins and
66 Sutton, 2009, 2010). Future ET_0 projections have been shown to depend on ET_0 estimation
67 methods in addition to GCMs. For example, Wang et al. (2015) used projections from the
68 CMIP3 HADCM3 model A2 scenario and found that the physically-based Penman-Monteith
69 equation, which uses less reliable GCM projection data (including vapor pressure and solar
70 radiation), and the empirical temperature-based Hargreaves equation showed similar patterns but
71 different magnitudes for future ET_0 changes over the Hanjiang River Basin in China. Kingston et
72 al. (2009) used 5 GCMs from the CMIP3 climate projections and 6 different ET_0 equations to
73 estimate global ET_0 and found that the choice of ET_0 method contributes to different projections
74 of the future state of water resources which varies by region. They found that the Hamon and
75 Jensen-Haise ET_0 estimates showed the greatest changes in both humid and arid regions while
76 the Penman-Monteith and Priestley-Taylor estimates frequently showed smallest change.
77 Similarly McAfee (2013) used three ET_0 equations with 17 CMIP3 GCMs to evaluate the
78 uncertainty of future global ET_0 projections and found that the Hamon equation showed more
79 significant and consistently positive trends in ET_0 compared to the Priestley-Taylor and Penman
80 methods.

81 Models developed to estimate future water supply and demand as a result of projected
82 climate change use many different types of ET_0 estimation methods (Zhao et al., 2013). Because
83 the choice of ET_0 estimation method may be as important as the choice of GCM or RCP
84 trajectory, better understanding of the contribution of each of these factors to the overall
85 prediction uncertainty of future water availability or water deficit is necessary (Taylor et al.,

86 2013). Kay and Davies (2008) compared the performance of the Penman-Monteith equation and
87 a simple temperature-based ET_0 method using climate data from five global and eight regional
88 climate models over Britain. They found that the two methods showed very different changes in
89 ET_0 for the period 2071-2100 under the A2 emission scenario, and different flow predictions for
90 three catchments when the data were used to force a rainfall-runoff model. Kay and Davies
91 results suggest that hydrological prediction uncertainty due to ET_0 formulation was smaller than
92 that due to GCM structure or RCM structure for their study region. Bae et al. (2011) evaluated
93 the uncertainty contributed by choice of GCM and hydrologic model for the Chungju Dam basin,
94 Korea. They found that hydrologic model structural differences contributed greater uncertainty
95 than GCM selection to winter runoff prediction. Koedyk and Kingston (2016) found that for the
96 Waikaia River, New Zealand ET_0 method contributed more uncertainty than GCM selection
97 when predicting ET_0 , but that runoff predictions were more sensitive to GCMs than to ET_0
98 methods. Thompson et al. (2014) evaluated the effect of using different GCMs and different ET_0
99 methods on discharge predictions for the Mekong River in Southeast Asia and found that GCM-
100 related uncertainty was greater than the ET_0 method related uncertainty.

101 **In this study we perform a comprehensive evaluation of the relative sensitivity of future**
102 **P, ET_0 and water deficit (defined here as $P - ET_0$) projections to choice of GCM, ET_0 method and**
103 **RCP trajectory over the continental USA using CMIP5 GCM model outputs to provide new**
104 **insights that will inform more robust future water resource planning efforts.** Variance-based
105 global sensitivity analysis (Saltelli et al., 2010) and Monte Carlo Filtering (Rose et al., 1991) are
106 used to quantify the uncertainty and important input factors controlling these projections. Global
107 sensitivity analysis (GSA) apportions the total output uncertainty simultaneously onto all the
108 uncertain input factors described by marginal probability density functions, and thus is preferred
109 over the local, one factor at a time, sensitivity analyses that have been previously reported
110 (Homma and Saltelli, 1996; Saltelli, 1999). Monte Carlo Filtering can identify sets of model
111 simulations and input factors that meet a specified criteria or threshold. Thus global sensitivity
112 analysis and Monte Carlo Filtering offer an opportunity to gain insight into the sources of
113 uncertainty, and drivers of particular types of wet/dry behavior, when estimating future water
114 deficit under projected climate change.

115

116 2. Methods

117 All retrospective and future climate variables were obtained from the CMIP5 archive
118 (accessible for download at <http://pcmdi9.llnl.gov/>). The “historical” runs of CMIP5 were used
119 for the retrospective period (1950-2005) and the same ensemble member runs (r1i1p1 ensemble)
120 of CMIP5 were used for two future periods: future period 1 (2030-2060), and future period 2
121 (2070-2100). Data for three RCP trajectories, RCP2.6, RCP4.5 and RCP8.5 were included in the
122 analyses. Taylor et al. (2012) described an overview of CMIP5 and RCP trajectories and
123 compared the differences between CMIP5 and CMIP3 model projections.

124 Data from the CMIP5 archive were used to calculate monthly mean P, ET_0 , and P- ET_0
125 (water deficit) for the retrospective and both future periods over each of the nine U.S. climate
126 regions identified by the National Climatic Data Center (Karl and Koss, 1984 (Fig. 1)). Future
127 changes in monthly mean P, ET_0 , and P- ET_0 were estimated by subtracting the monthly mean
128 value for the retrospective period from the monthly mean value for future period 1 or future
129 period 2, as appropriate (Baker and Huang, 2014).

130 Ten commonly used reference evapotranspiration estimation methods (Hargreaves,
131 Blaney-Criddle, Hamon, Kharrufa, Irmak-Rn, Irmak-Rs, Dalton, Meyer, Penman-Monteith and
132 Priestley-Taylor) were used in this study. The methods can be further classified into temperature-
133 (Hargreaves, Blaney-Criddle, Hamon and Kharrufa), radiation (Irmak-Rn, Irmak-Rs and
134 Priestley-Taylor), mass transfer (Dalton and Meyer), and combination (Penman-Monteith)
135 equations. These equations are well-described in many papers (e.g., Allen et al., 1998;
136 Hargreaves and Allen, 2003; Irmak et al., 2003; Tabari, 2010; Tabari et al., 2013; Xu and Singh,
137 2001) and are summarized in Table 1 (hereafter precipitation is referred to as P, and reference
138 evapotranspiration is referred to as ET_0 for convenience).

139 Variables directly used from the CMIP5 monthly model output included precipitation (pr,
140 P in this study), maximum and minimum temperature (tasmax and tasmin), radiation (rlds, rlus,
141 rsds, and rsus), air pressure (psl and ps), and wind speed (sfcWind). The abbreviations for these
142 variables are as defined in the CMIP5 archive and explained in the PCMDI server (Program For
143 Climate Model Diagnosis and Intercomparison, [http://cmip-
144 pcmdi.llnl.gov/cmip5/docs/standard_output.pdf](http://cmip-pcmdi.llnl.gov/cmip5/docs/standard_output.pdf)). Other variables needed in the ten reference

145 evapotranspiration equations were calculated using the variables from CMIP5 monthly model
 146 output (for details see Table 1). Monthly output that included all the variables needed for the
 147 Penman-Monteith reference evapotranspiration method (the most data intensive method) was
 148 available for both the retrospective period, and for the RCP2.6, RCP 4.5, and RCP8.5 trajectories
 149 for the future periods, for 9 CMIP5 models. Table 2 lists the 9 models from the CMIP5 archive
 150 that were used in this study.

151 The sensitivity of changes in future P, ET_0 and water deficit (defined here as $P - ET_0$) to
 152 the choice of GCM, ET_0 estimation method, and RCP trajectory was evaluated using the
 153 variance-based GSA method of Saltelli et al. (2010). Given a model of the form $Y =$
 154 $f(X_1, X_2, \dots, X_k)$, with Y a scalar, the variance-based first order effect for a generic factor X_i can
 155 be written (Saltelli et al., 2010):

$$156 \quad V_{X_i} \left(E_{X_{\sim i}}(Y|X_i) \right) \quad (1)$$

157 where X_i is the i -th factor (in our case either GCM, ET_0 method or RCP trajectory) and $X_{\sim i}$ is the
 158 vector of all factors except X_i . The expectation operator $E_{X_{\sim i}}(Y|X_i)$ indicates that the mean of
 159 Y is taken over all possible values of X except X_i (i.e. $X_{\sim i}$) while keeping X_i fixed. The variance,
 160 V_{X_i} , is then taken of this quantity over all possible values of X_i .

161 The first order sensitivity coefficient is expressed as:

$$162 \quad S_i = \frac{V_{X_i}(E_{X_{\sim i}}(Y|X))}{V(Y)} \quad (2)$$

163 Where $V(Y)$ the total variance of Y over all X_i . S_i is a normalized index varying between 0 and
 164 1, because $V_{X_i} \left(E_{X_{\sim i}}(Y|X_i) \right)$ varies between 0 and $V(Y)$ according to the identity (Mood et al.,
 165 1974):

$$166 \quad V_{X_i} \left(E_{X_{\sim i}}(Y|X_i) \right) + E_{X_i} \left(V_{X_{\sim i}}(Y|X_i) \right) = V(Y) \quad (3)$$

167 As indicated above $V_{X_i} \left(E_{X_{\sim i}}(Y|X_i) \right)$ is the first order effect of X_i on the model output
 168 Y , while $E_{X_i} \left(V_{X_{\sim i}}(Y|X_i) \right)$ is called the residual. The total effect index, including first order and

169 higher order effects (i.e. interactions between factor X_i and other factors) of the factor X_i on the
 170 model output is calculated (Saltelli et al., 2010):

$$171 \quad S_{T_i} = \frac{E_{X \sim i}(V_{X_i}(Y|X_{\sim i}))}{V(Y)} = 1 - \frac{V_{X \sim i}(E_{X_i}(Y|X_{\sim i}))}{V(Y)} \quad (4)$$

172 The first order sensitivity of estimated future changes in mean monthly P, ET_0 , and P-
 173 ET_0 to choice of GCM, ET_0 estimation method and RCP trajectory were calculated over the nine
 174 US climate regions for each future period in order to evaluate the relative contributions of each
 175 of these factors on the uncertainty of future changes. A total of 270 simulations (9 GCMs \times 10
 176 evapotranspiration methods \times 3 RCP trajectories) was used in the analysis. Sensitivity of
 177 projected changes in P were evaluated for both choice of GCM and choice of RCP trajectory.
 178 Sensitivity of projected changes in ET_0 and P- ET_0 were evaluated for choice of GCM, choice of
 179 ET_0 estimation method, and choice of RCP trajectory.

180 For projected changes in water deficit (P- ET_0) Monte Carlo filtering (Saltelli et al., 2008)
 181 was used to identify whether projected wetter or drier future conditions (i.e. larger or smaller
 182 water deficit) could be attributed to specific GCMs, ET_0 estimation methods, or RCP trajectories.
 183 For each future period the ensemble of 270 projections of change in water deficit were
 184 categorized as either wet future condition (mean change in $(P - ET_0) \geq 0$) or dry future
 185 condition (mean change in $(P - ET_0) < 0$). Next for each factor (X_i =GCM, ET_0 method, RCP
 186 trajectory) the histograms of wet ($f_{wet}|X_i$) and dry ($f_{dry}|X_i$) future conditions over the range of
 187 possible values of that factor were estimated. To identify the factors that are most responsible for
 188 driving the model into projected wet or dry future conditions for each factor, X_i , the distributions
 189 ($f_{wet}|X_i$) and ($f_{dry}|X_i$) were tested for significant difference using the X^2 two sample test for
 190 categorical variables with $\alpha=0.05$ (Rao and Scott, 1981). If for a given factor X_i the two
 191 distributions are significantly different, then X_i is a key factor in driving into either a wet or dry
 192 condition (Saltelli et al., 2008).

193 Because GCM predictions are known to contain systematic biases (Hwang and Graham,
 194 2013; Wood et al., 2002, 2004) we evaluated the sensitivity of the mean monthly change in raw
 195 climate predictions between retrospective and future periods to the choice of GCM, ET_0
 196 estimation method and RCP trajectories. This is analogous to using the delta change GCM bias

197 correction method that involves shifting the mean of a series of observed climate data by the
198 mean difference in raw GCM output between the corresponding observed time period and the
199 desired future period. Teutschbein and Seibert (2012) pointed out that all bias correction methods
200 are based on the stationarity principle that assumes that similar biases occur in the retrospective
201 and future predictions and thus the same bias-correction algorithm may be applied to both.
202 Muerth et al. (2013) found that the impact of bias correction on the relative change of flow
203 indicators between retrospective and future periods was weak for most indicators, however
204 Pierce et al. (2015) found that some bias correction methods altered model-projected changes in
205 mean precipitation and temperature. LaFond et al. (2014) found that the delta change GCM bias
206 correction method was more useful for simulating hydrologic extreme events than the quantile
207 mapping bias correction method as it preserved daily climate variability better. In this study, we
208 differenced raw rather than bias corrected GCM outputs in order to prevent spurious alteration of
209 the climate change signal between retrospective and future GCMs that might be induced by the
210 bias correction method.

211

212 **3. Results**

213 **3.1. Projected P, ET₀, and water deficit change in the 21st century**

214 Future P, ET₀ and water deficit projections include large uncertainties stemming from
215 different sources. Figures 2 and 3 present maps of the mean change (Fig. 2) and the standard
216 deviation of change (Fig. 3) in annual P (top chart), ET₀ (middle) and water deficit (P – ET₀;
217 bottom) over the continental US calculated over all GCMs, ET₀ estimation methods, and RCP
218 trajectories for future period 2 (2070-2100). Major portions of the West, Southwest and South
219 show a mean decrease in annual precipitation, while the rest of the continental US shows a mean
220 increase (Fig. 2 (a)). Future annual ET₀ shows a mean increase over retrospective annual ET₀
221 over the entire US (Fig. 2 (b)), with the largest increase in the South region. Following the
222 patterns of P and ET₀, future annual water deficit (P – ET₀) shows a significant mean decrease in
223 the West, Southwest and South regions and a slight decline, or negligible change in most other
224 regions (Fig. 2 (c)). These mean changes in annual P, ET₀ and P- ET₀ are relatively small
225 compared to the standard deviation of changes in annual P, ET₀, and P – ET₀ (Fig. 3). Water

226 deficit in particular has a large standard deviation, resulting in coefficients of variation larger
227 than one throughout the continental US. Similar results are shown in the Fig. S-1 and Fig. S-2 for
228 future period 1 (2030-2060) in the supplemental materials.

229 Figure 4 shows the seasonal changes in the monthly mean and standard deviation of
230 water deficit ($P - ET_0$) over the nine US regions. Blue and red lines represent the changes in
231 monthly mean water deficit for future period 1 and future period 2, respectively and the error
232 bars represent one standard deviation around each mean value. All regions of the continental US
233 show drier conditions (negative mean changes) in the summer season (Jun – Aug). Southern
234 regions (Southeast, South, Southwest and West) show drier conditions throughout the year,
235 however northern portions of the US (i.e. the Northeast, Ohio Valley, Upper Midwest, Northern
236 Rockies and Plains and Northwest) show wetter conditions (positive mean changes) in the winter
237 season.

238 3.2. Global sensitivity analysis of projected changes

239 Figure 5 shows the first order sensitivity of change in P to GCM and RCP trajectory over
240 the nine US climate regions for future periods 1 and 2. For projected changes in P, the choice of
241 GCM is generally more important than choice of RCP trajectory for all regions and both future
242 periods. First order sensitivities of mean change in ET_0 to GCM, ET_0 method and RCP
243 trajectory are shown in Fig. 6. This figure clearly shows that the choice of ET_0 method is the
244 most influential factor for projecting change in ET_0 for both future periods, except for the month
245 of March in the Northeast, Upper Midwest and Northern Rockies and Plains. High sensitivity of
246 mean change in ET_0 to GCM selection occurs in spring for several regions (Northeast, Upper
247 Midwest and Northern Rockies and Plains), indicating a divergence of model predictions during
248 this time. The influence of the RCP trajectory on ET_0 increases in future period 2 over future
249 period 1, with a concomitant decrease in the influence of both ET_0 method and GCM. In future
250 period 1 the GCM sensitivity coefficients are greater than the RCP trajectory sensitivity
251 coefficients over most regions; however, in future period 2 the RCP sensitivity coefficients
252 become more important. Figure 7 shows that projected change in water deficit depend strongly
253 on both the choice of GCM and ET_0 estimation method. In all regions except the Southeast
254 projected change in water deficit is most sensitive to ET_0 estimation method in the warm season
255 (May through October) and most sensitive to GCM in the cool season (December through

256 March). For the Southeast region the sensitivity coefficients for GCM and ET₀ method are quite
257 similar throughout the year. The sensitivity coefficients for RCP trajectory are very low in future
258 1, but increase in future 2, becoming approximately equal to the GCM sensitivity coefficients in
259 the summer season in future 2.

260 3.3. Change in annual mean water deficit projections using different ET₀ methods

261 Figure 8 shows the change in annual mean water deficit over all 9 GCMs for the RCP 4.5
262 trajectory in future period 1 (2030-2060) predicted by the ten different ET₀ methods used in this
263 study (a: Hargreaves, b: Blaney-Criddle, c: Hamon, d: Kharrufa, e: Irmak-Rn, f: Irmak-Rs, g:
264 Dalton, h: Meyer, i: Penman-Monteith, j: Priestley-Taylor). This figure clearly shows that the
265 changes in water deficit for future period 1 are diverse and depend strongly on the choice of ET₀
266 method. Except for the Hargreaves method (Fig. 8a) the temperature based methods (e.g.
267 Blaney-Criddle (Fig. 8b), Hamon (Fig. 8c) and Kharrufa (Fig. 8d)) predict drier conditions over
268 the continental US than the other methods. The mass transfer based methods (e.g Dalton (Fig.
269 8g) and Meyer (Fig. 8h)) predict generally wetter conditions over most of the continental US
270 compared to other methods. The combination method (Penman Monteith (Fig. 8i)), and the
271 radiation based methods (Irmak-Rn (Fig 8e), Irmak-Rs (Fig. 8f) and Priestley Taylor (Fig. 8j))
272 generally fall between the mass transfer based and temperature based methods, with the
273 combination methods producing slightly drier conditions. Although most methods predict similar
274 spatial patterns of water deficit over the continental US (generally drier conditions in the West,
275 Southwest and South and generally wetter elsewhere), the Hamon method predicts a different
276 pattern of water deficit over the Southwest, South and Northern Rockies and Plains regions.

277 3.4. Monte Carlo filtering

278 Monte Carlo filtering (Saltelli et al., 2008) was conducted to further investigate whether
279 projected wetter or drier future conditions (i.e. larger or smaller annual mean water deficit) could
280 be attributed to specific GCMs, ET₀ estimation methods, or RCP trajectories. Figures 9 shows
281 the histograms for wet conditions and dry conditions in future 2 over the Southeast US by GCM,
282 ET₀ method and RCP trajectory for the example month of July. Figure 10 shows similar
283 histograms for the Northern Rockies and Plains, a region with differing behavior from the
284 Southeast US. Table 3 shows the P-value results for the X^2 - test for all months in both futures for

285 the Southeast and Northern Rockies and Plains regions. P-values greater than 0.05 (shaded in
286 grey) indicate the two histograms are not significantly different from each other. Tables 4 – 6
287 show the fraction of time that a particular GCM (Table 4), ET₀ method (Table 5), or RCP
288 trajectory (Table 6) projected drier future conditions in each of the nine US climate regions for
289 each month, with fractions higher than 0.5 shaded in grey.

290

291 **4. Discussion**

292 Drier conditions in southern regions (Southeast, South, Southwest and West) and wetter
293 conditions in northern regions (Northeast, Ohio Valley, Upper Midwest, Northern Rockies and
294 Plains and Northwest) are consistent (Fig. 4) with those reported by McAfee (2013) who used 3
295 ET₀ methods (Hamon, Priestley-Taylor and Penman-Monteith) to estimate global changes in ET₀
296 over the entire globe. As found by Baker and Huang (2014) for both CMIP3 and CMIP5
297 projections, mean ET₀ is projected to be higher in future period 2 than in future period 1, and
298 mean precipitation projections are approximately equivalent in future period 1 and future period
299 2. Thus the projected mean changes in water deficit for future period 2 (red lines in Fig. 4) are
300 larger in magnitude than the projected changes for future period 1 (blue lines). In all regions, and
301 for both future periods, the one standard deviation error bars bracket zero mean change
302 indicating large uncertainty in the projections throughout the year.

303 The choice of GCM is generally more important than the choice of RCP trajectory for
304 projected changes in P (Fig. 5). This is consistent with results found by Gaetani and Mohino
305 (2013) and Knutti and Sedláček (2012) who showed significant differences in precipitation
306 predictions among CMIP5 models. It should be noted that these results do not indicate that the
307 choice of RCP trajectory does not affect the change in precipitation, only that the choice of RCP
308 trajectory is less influential than the choice of GCM. There are no consistent seasonal patterns of
309 the first-order sensitivity coefficients for either GCM or RCP trajectory in either future period.
310 However, during the spring months, the sensitivity of change in P to choice of RCP trajectory
311 increases substantially in future 2 compared to future 1 in the Northeast, Ohio Valley, Upper
312 Midwest, South, Southwest and West regions.

313 Higher sensitivity of mean change in ET_0 to the choice of ET_0 estimation method than the
314 choice of GCM (Fig. 6) are consistent with those found by Kingston et al. (2009) who showed
315 that projected increase in ET_0 varied by more than 100% between ET_0 methods, and Schwalm et
316 al. (2013) who found the choice of ET_0 estimation method is sensitive and even more influential
317 than the choice of GCM in predicting ET_0 . However, neither of these studies looked at the
318 influence of RCP trajectory on ET_0 projections, which increases in future period 2 over future
319 period 1, causing a decrease in the sensitivity coefficient of both GCM and ET_0 method in future
320 2. Burke and Brown (2008) evaluated uncertainties in the projection of future drought using
321 several drought indices. They found that there are large uncertainties in regional changes in
322 drought and changes in drought are dependent on both index definition and GCM ensemble
323 members. Similarly, our results for the projected change in water deficit vary by region, depend
324 strongly on the choice of GCM and ET_0 estimation method, but are relatively less sensitive to
325 RCP trajectory (Fig. 7). These findings are similar to results reported by Orłowski and
326 Seneviratne (2013) who found that the greenhouse gas emission scenario uncertainty is not as
327 important as differences among GCMs or internal climate variability when predicting
328 Standardized Precipitation Index (SPI) and soil moisture (SMA). However, they also found that
329 uncertainty due to greenhouse gas emission scenario increased in later future periods. Taylor et
330 al. (2013) showed the patterns of changes in future drought were similar between the A1B
331 scenario in CMIP3 and the RCP2.6 trajectory in CMIP5, reinforcing our finding that the choice
332 of RCP trajectory is less important than the choice of GCM and ET_0 estimation method when
333 estimating future water deficit.

334 Similar to the results of Kay and Davies (2008) and Bae et al. (2011) the results of our
335 GSA show that the choice of ET_0 method has important implications when making future ET_0
336 projections and future water deficit projections (Fig. 8). Kingston et al. (2009) recommended the
337 use of different ET_0 equations to evaluate global ET_0 , and Wang et al. (2015) found that although
338 different methods predict similar future ET_0 , there are important differences in uncertainties due
339 to ET_0 estimation methods and input data reliability. Currently many hydrological models use a
340 single evapotranspiration method for simulation, which may substantially increase the
341 uncertainty and reduce the reliability of future projections. Our results strongly indicate that an
342 ensemble of ET_0 estimation methods should be used to understand potential future water
343 availability and water deficit due to climate change.

344 Monte Carlo filtering results (Fig. 9 and 10, Table 3) indicate that GCM and ET₀ methods
345 both produce statistically significant different wet condition and dry condition histograms in both
346 the Southeast and Northern Rockies and Plains regions for almost all months in both future
347 periods. This indicates that particular GCMs and ET₀ methods tend to systematically produce
348 wet or dry conditions. Some GCMs (i.e. MIROC_ESM and BCC-CSM (Table 4)) and ET₀
349 methods (i.e. Priestley-Taylor, Blaney-Criddle, and Kharrufa (Table 5)) predict dry conditions a
350 majority of the time for all regions in both future periods. However, the remaining GCMs and
351 ET₀ methods project both wetter or drier futures depending on the region and future period.
352 Results in Tables 4 through 6 show that for the South, West and Southwest regions drier
353 conditions are predicted a majority of the time in both future periods by all GCMs and RCP
354 trajectories, and all ET₀ methods except Hargreaves. For RCP trajectory, P-values indicate the
355 histograms are statistically significantly different in fewer cases than for either GCM or ET₀
356 method for both future 1 and 2 (Table 3). These results are consistent with the first order
357 sensitivity coefficients results that showed the RCP trajectory is not as important a factor as
358 GCM or ET₀ method in driving differences in future projections, but that the sensitivity to choice
359 of RCP trajectory increases in future period 2.

360 GCMs estimate some climate variables, such as temperature, with higher confidence than
361 other variables (Randall et al., 2007). However, for some evapotranspiration estimation methods
362 the effect of temperature on evaporation is smaller than other climate variables (Linacre, 1994;
363 Roderick et al., 2009a, 2009b; Thom et al., 1981). We found that temperature and net radiation
364 from the CMIP5 GCMs show increasing trends over the 2005-2100 time period, while wind
365 speed and surface pressure are relatively constant (Fig. S-3). Because we considered various ET₀
366 estimation methods our results include the impacts of the different physics represented in the ET₀
367 methods, the projected changes each of the climate variables contributing to the different ET₀
368 methods, and the reliability of the predictions of each variable.

369

370 **5. Summary and conclusions**

371 Future changes in precipitation and evapotranspiration will lead to changes in the
372 hydrologic balance. This study clearly shows that the uncertainty caused by different GCMs, ET₀

373 methods, and RCP trajectories make actionable water resources planning based on climate
374 change projections difficult. Understanding and quantifying how these projected changes vary
375 with choice of GCM, ET_0 method and RCP trajectory is important for designing robust
376 ensembles of scenarios to include in future water resources planning. This study assessed the
377 future mean change in monthly precipitation, evapotranspiration and water deficit ($P - ET_0$)
378 projected by CMIP5 simulations over the continental US and analyzed the sensitivity of the
379 projected changes to the choice of GCM, ET_0 estimation method, and RCP trajectory. Nine
380 GCMs, ten ET_0 estimation methods, and three RCP trajectories were included in the analyses.
381 Variance-based global sensitivity analysis (Saltelli et al., 2010) was conducted in order to
382 determine the relative contributions of the choice of GCMs, ET_0 estimation methods, and RCP
383 trajectory to uncertainty in future prediction. Monte Carlo filtering was used to investigate
384 whether particular GCMs, ET_0 methods, and/or RCP scenarios consistently led to wet or dry
385 future projections.

386 The global sensitivity analyses showed that projected changes in precipitation are more
387 sensitive to the choice of GCM than the choice of RCP trajectory over the entire continental US
388 for both future periods. However, the choice of RCP trajectory becomes more important in future
389 period 2. The most sensitive factor for the future ET_0 projections is the choice of ET_0 estimation
390 method for all regions in both future periods. The first order sensitivity of projected change in
391 future ET_0 to choice of RCP trajectory increases in future period 2 compared to future 1, with a
392 concomitant decrease in the first order sensitivity to the choice of GCM. For projected change in
393 future water deficit the choice of ET_0 method constitutes the dominant source of uncertainty in
394 warmer months (May through September) and the choice of GCM is the dominant source of
395 uncertainty in the cooler months (November through March) over all regions except the
396 Southeast where the sensitivity of GCM and ET_0 method are roughly equal throughout the year.
397 Sensitivity of change in future water deficit to RCP trajectory is very small for future period 1,
398 but increased in future period 2.

399 Monte Carlo filtering results indicated that both GCMs and ET_0 methods produced
400 statistically different histograms for wetter or drier future conditions (i.e. larger or smaller mean
401 future water deficit) for almost all months in both future periods. Two GCMs (MIROC_ESM
402 and BCC-CSM) and three ET_0 methods (Priestley-Taylor, Blaney-Criddle, and Kharrufa)

403 predicted dry conditions a majority of the time for all regions in both future periods; however,
404 the remaining GCMs and ET₀ methods projected both wetter and drier futures depending on the
405 region.

406 Results of this study indicate that when predicting the effects of future climate on water
407 resources the choice of evapotranspiration method should be carefully evaluated. Rather than the
408 typical practice of using a single ET₀ method to drive a hydrologic model with future climate
409 projections, an ensemble of ET₀ methods should be used in addition to an ensemble of GCMs
410 and a variety of RCP trajectories. The GSA methodology adopted here assumed that all the
411 GCMs, ET₀ methods and RCP trajectories used in this study were equally appropriate for use in
412 all US regions (i.e. the sensitivity coefficients were evaluated by equally weighting each GCMs,
413 ET₀ method and RCP trajectory) which is likely not to be the case. When making future
414 projections potential climate change on water resources Reliability Ensemble Averaging (REA)
415 (Giorgi and Mearns, 2002) or Bayesian-based indicator-weighting (Asefa and Adams, 2013;
416 Tebaldi et al., 2005; Xing et al., 2014) could be used to weight the results of an ensemble of
417 GCMs and ET methods based on how close the retrospective GCM- ET₀ method predictions
418 agree with past observations (bias criterion) and how well the future GCM- ET₀ -RCP
419 projections agree with other future GCM- ET₀ -RCP predictions (convergence criterion).

420 This study assumed that ET₀ methods that have been developed and parameterized based
421 on vegetation response to current CO₂ levels and climatic conditions will be valid under future
422 CO₂ levels and climatic conditions. Future research should explore the validity of this
423 assumption by incorporating potential changes in plant transpiration (e.g. stomatal conductance)
424 to changing CO₂ levels into the ET₀ estimation methodologies.

425

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628

629

630 Table 1. Description of reference evapotranspiration estimation methods used in this study (ET₀:
631 Reference evapotranspiration).

Methods	Equations ¹	Reference
(a) Hargreaves	$ET_0 = 0.0135K_T S_0 (T + 17.8) \sqrt{\delta_T}$	Hargreaves and Allen (2003)
(b) Blaney-Criddle	$ET_0 = p(0.46T + 8.13)$	Xu and Singh (2002)
(c) Hamon	$ET_0 = 0.55\delta_T^2 P_t$	Xu and Singh (2002)
(d) Kharrufa	$ET_0 = 0.34pT^{1.3}$	Xu and Singh (2002)
(e) Irmak-Rn	$ET_0 = 0.486 + 0.289R_n + 0.023T$	Irmak et al. (2003)
(f) Irmak-Rs	$ET_0 = -0.611 + 0.149R_s + 0.079T$	Irmak et al. (2003)
(g) Dalton	$ET_0 = (0.3648 + 0.07223u)(e_s - e_a)$	Tabari et al. (2013)
(h) Meyer	$ET_0 = (0.375 + 0.05026u)(e_s - e_a)$	Tabari et al. (2013)
(i) Penman-Monteith	$ET_0 = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T + 273} u_2 (e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)}$	Allen et al. (1998)
(j) Priestley-Taylor	$ET_0 = \alpha \frac{\Delta}{\Delta + \gamma} \frac{(R_n - G)}{\lambda}$	Allen et al. (1998)

632 ¹Variables (estimated from CMIP5 outputs): G: Soil heat flux (assumed 0); γ : Psychrometric constant; T: Average
633 temperature; u_2 : Wind speed at 2m surface; e_s : Saturated vapor pressure; e_a : Actual vapor pressure; Δ : Slope vapor
634 pressure; K_T : Hargreaves-Samani coefficient; S_0 : Extraterrestrial radiation (estimated by Julian date); δ_T : Difference
635 between maximum and minimum temperature, p: Percentage of total daytime hours (Estimated by Julian date); R_n :
636 Net radiation; R_s : Solar radiation; P_t : Saturated water vapor density; u: Wind speed

637 Table 2. Description of the CMIP5 models used in this study.

Model	Institute (country)	Resolutions	Calendar	Reference
(1) BNU-ESM	College of Global Change and Earth System Science, Beijing Normal University (China)	2.8° lat × 2.8° lon	No leap	Ji et al. (2014)
(2) CSIRO-MK3-6-0	University of New South Wales (Australia)	1.87° lat × 1.87° lon	No leap	Rotstayn et al. (2012)
(3) GFDL-CM3	NOAA/Geophysical Fluid Dynamics Laboratory (USA)	2.0° lat × 2.5° lon	No leap	Guo et al. (2014)
(4) GFDL-ESM2G	NOAA/Geophysical Fluid Dynamics Laboratory (USA)	2.0° lat × 2.5° lon	No leap	Taylor et al. (2012)
(5) MIROC-ESM	Atmosphere and Ocean Research Institute, National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology (Japan)	2.8° lat × 2.8° lon	Leap year	Watanabe et al. (2011)
(6) MPI-ESM-LR	Max Planck Institute for Meteorology (Germany)	1.87° lat × 1.87° lon	Leap year	Block and Mauritsen (2013)
(7) MRI-CGCM3	Meteorological Research Institute (Japan)	1.12° lat × 1.12° lon	Leap year	Yukimoto et al. (2012)
(8) NorESM1-M	Norwegian Climate Centre (Norway)	1.9° lat × 2.5° lon	No leap	Bentsen et al. (2013)
(9) BCC-CSM1.1	Beijing Climate Center (China)	2.8° lat × 2.8° lon	No leap	Xiao-Ge et al. (2013)

638

639 Table 3. P-values of Chi-square two sample test for difference among wet condition versus dry
 640 condition pdfs Southeast U.S (SE US) and Northern Rockies and Plains (NRP; West North
 641 Central) U.S. (Shaded cells indicate pdfs are not statistically significantly different at p=0.05)

Month		Future 1			Future 2		
		GCM	ET ₀	RCP	GCM	ET ₀	RCP
SE US	1	0.0000	0.0689	0.3701	0.0000	0.1823	0.1853
	2	0.0000	0.0889	0.4434	0.0000	0.0269	0.0000
	3	0.0000	0.0365	0.0306	0.0000	0.0000	0.1339
	4	0.0000	0.0000	0.6602	0.0000	0.0000	0.0001
	5	0.0000	0.0000	0.3223	0.0000	0.0000	0.0041
	6	0.0000	0.0000	0.0809	0.0000	0.0000	0.0006
	7	0.0000	0.0000	0.2855	0.0000	0.0000	0.0749
	8	0.0000	0.0000	0.2805	0.0000	0.0000	0.0074
	9	0.0000	0.0000	0.8646	0.0000	0.0000	0.0044
	10	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001
	11	0.0000	0.0001	0.0000	0.0000	0.0001	0.2003
	12	0.0000	0.0117	0.3083	0.0000	0.0000	0.0000
NRP	1	0.0000	0.0000	0.1931	0.0000	0.0000	0.0000
	2	0.0000	0.0000	0.0010	0.0000	0.0000	0.7617
	3	0.0000	0.0000	0.0538	0.0000	0.0000	0.0769
	4	0.0000	0.0000	0.7882	0.0002	0.0000	0.8925
	5	0.0000	0.0000	0.4047	0.0000	0.0000	0.1103
	6	0.0000	0.0000	0.3839	0.0000	0.0000	0.0000
	7	0.0000	0.0000	0.5321	0.0001	0.0008	0.0000
	8	0.0000	0.0001	0.1544	0.0000	0.0686	0.0000
	9	0.0000	0.0000	0.4242	0.0000	0.0000	0.2002
	10	0.0000	0.0000	0.6688	0.0000	0.0213	0.0001
	11	0.0000	0.0000	0.1334	0.0000	0.0000	0.1948
	12	0.0000	0.0000	0.7617	0.0000	0.0000	0.6561

642

643

644 Table 4. The fraction of future dry conditions over all months by GCM (Future period 1 and 2).

	GCM	SE	South	West	NR	NE	NW	UM	SW	Ohio
Future period 1 - Dry condition	BNU_ESM	0.575	0.589	0.511	0.367	0.436	0.322	0.467	0.453	0.492
	CSIRO_mk3_6_0	0.489	0.689	0.639	0.547	0.297	0.519	0.381	0.653	0.481
	GFDL_CM3	0.414	0.608	0.686	0.419	0.403	0.525	0.383	0.647	0.425
	GFDL_ESM2G	0.731	0.900	0.758	0.453	0.486	0.486	0.397	0.828	0.617
	MIROC_ESM	0.631	0.594	0.822	0.625	0.636	0.708	0.686	0.658	0.611
	MPI_ESM_LR	0.375	0.747	0.694	0.542	0.597	0.611	0.558	0.756	0.575
	MRI_CGCM3	0.494	0.592	0.639	0.400	0.544	0.553	0.350	0.547	0.506
	NorESM1_M	0.492	0.764	0.778	0.475	0.400	0.611	0.475	0.753	0.508
	BCC_CSM	0.728	0.739	0.828	0.642	0.603	0.614	0.564	0.822	0.656
Future period 2 - Dry condition	BNU_ESM	0.608	0.775	0.597	0.400	0.522	0.461	0.478	0.522	0.572
	CSIRO_mk3_6_0	0.367	0.667	0.583	0.528	0.225	0.528	0.433	0.633	0.461
	GFDL_CM3	0.467	0.767	0.789	0.461	0.514	0.542	0.508	0.794	0.469
	GFDL_ESM2G	0.722	0.831	0.694	0.478	0.519	0.525	0.397	0.672	0.581
	MIROC_ESM	0.672	0.686	0.897	0.742	0.731	0.728	0.700	0.739	0.664
	MPI_ESM_LR	0.442	0.800	0.778	0.519	0.542	0.639	0.450	0.800	0.450
	MRI_CGCM3	0.508	0.703	0.581	0.422	0.481	0.528	0.439	0.517	0.556
	NorESM1_M	0.594	0.808	0.722	0.500	0.461	0.550	0.481	0.731	0.594
	BCC_CSM	0.628	0.697	0.875	0.708	0.567	0.708	0.556	0.825	0.603

645

646

647 Table 5. The fraction of future dry condition over all months by ET₀ estimation method and
 648 region (Future period 1 and 2).

	ET ₀	SE	South	West	NR	NE	NW	UM	SW	Ohio
Future period 1 -Dry condition	Hargreaves	0.302	0.426	0.559	0.333	0.309	0.466	0.321	0.485	0.324
	Blaney_Criddle	0.738	0.880	0.898	0.840	0.738	0.762	0.784	0.904	0.769
	Hamon	0.633	0.818	0.667	0.531	0.494	0.497	0.457	0.713	0.549
	Kharrufa	0.883	0.957	0.889	0.636	0.667	0.698	0.636	0.886	0.738
	Irmak_Rn	0.522	0.673	0.694	0.491	0.512	0.556	0.494	0.679	0.580
	Irmak_Rs	0.525	0.722	0.731	0.463	0.485	0.546	0.460	0.679	0.556
	Dalton	0.364	0.503	0.583	0.340	0.343	0.426	0.296	0.509	0.380
	Meyer	0.367	0.531	0.596	0.346	0.324	0.435	0.290	0.512	0.367
	PM	0.534	0.685	0.694	0.472	0.469	0.525	0.481	0.676	0.540
	PT	0.608	0.719	0.750	0.515	0.552	0.590	0.515	0.753	0.608
Future period 2 -Dry condition	Hargreaves	0.352	0.506	0.605	0.420	0.355	0.491	0.380	0.537	0.361
	Blaney_Criddle	0.765	0.907	0.880	0.877	0.769	0.818	0.830	0.901	0.806
	Hamon	0.633	0.861	0.679	0.552	0.491	0.528	0.460	0.719	0.574
	Kharrufa	0.883	0.954	0.898	0.704	0.713	0.728	0.682	0.883	0.784
	Irmak_Rn	0.515	0.738	0.710	0.494	0.491	0.574	0.503	0.685	0.543
	Irmak_Rs	0.534	0.796	0.753	0.485	0.497	0.562	0.478	0.719	0.562
	Dalton	0.349	0.596	0.620	0.389	0.358	0.475	0.315	0.540	0.373
	Meyer	0.352	0.596	0.630	0.383	0.349	0.488	0.309	0.546	0.361
	PM	0.543	0.744	0.701	0.475	0.485	0.531	0.463	0.679	0.528
	PT	0.639	0.784	0.765	0.509	0.562	0.593	0.515	0.716	0.608

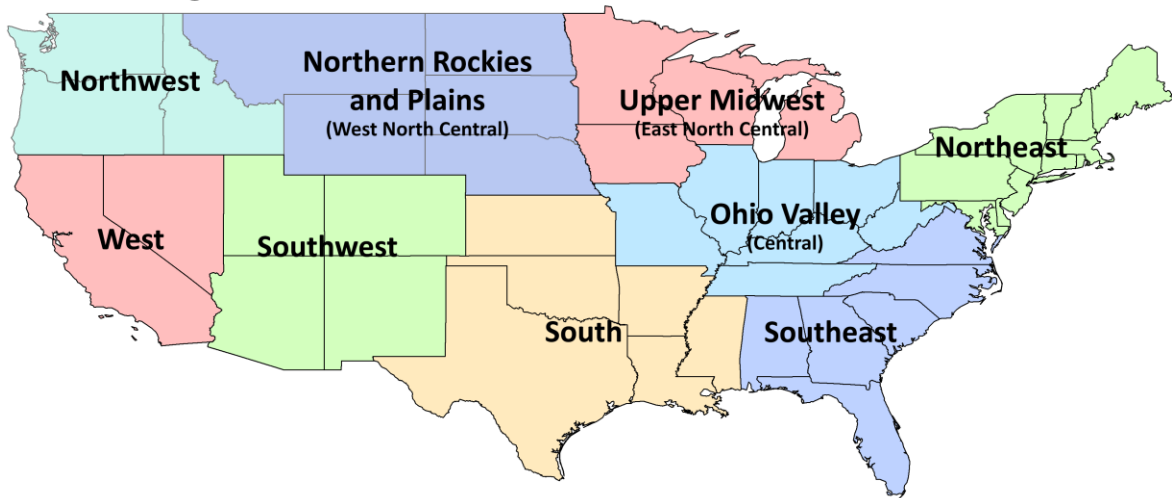
649

650 Table 6. The fraction of future dry condition over all months by RCP trajectory and region
 651 (Future period 1 and 2).

	RCP	SE	South	West	NR	NE	NW	UM	SW	Ohio
Future period 1 -Dry condition	2.6	0.551	0.657	0.665	0.507	0.502	0.543	0.495	0.644	0.553
	4.5	0.553	0.698	0.739	0.515	0.475	0.554	0.482	0.731	0.556
	8.5	0.539	0.719	0.715	0.468	0.491	0.554	0.443	0.665	0.515
Future period 2 -Dry condition	2.6	0.516	0.649	0.657	0.486	0.524	0.515	0.465	0.617	0.545
	4.5	0.490	0.731	0.712	0.510	0.476	0.584	0.494	0.658	0.528
	8.5	0.664	0.864	0.803	0.590	0.520	0.637	0.521	0.803	0.577

652

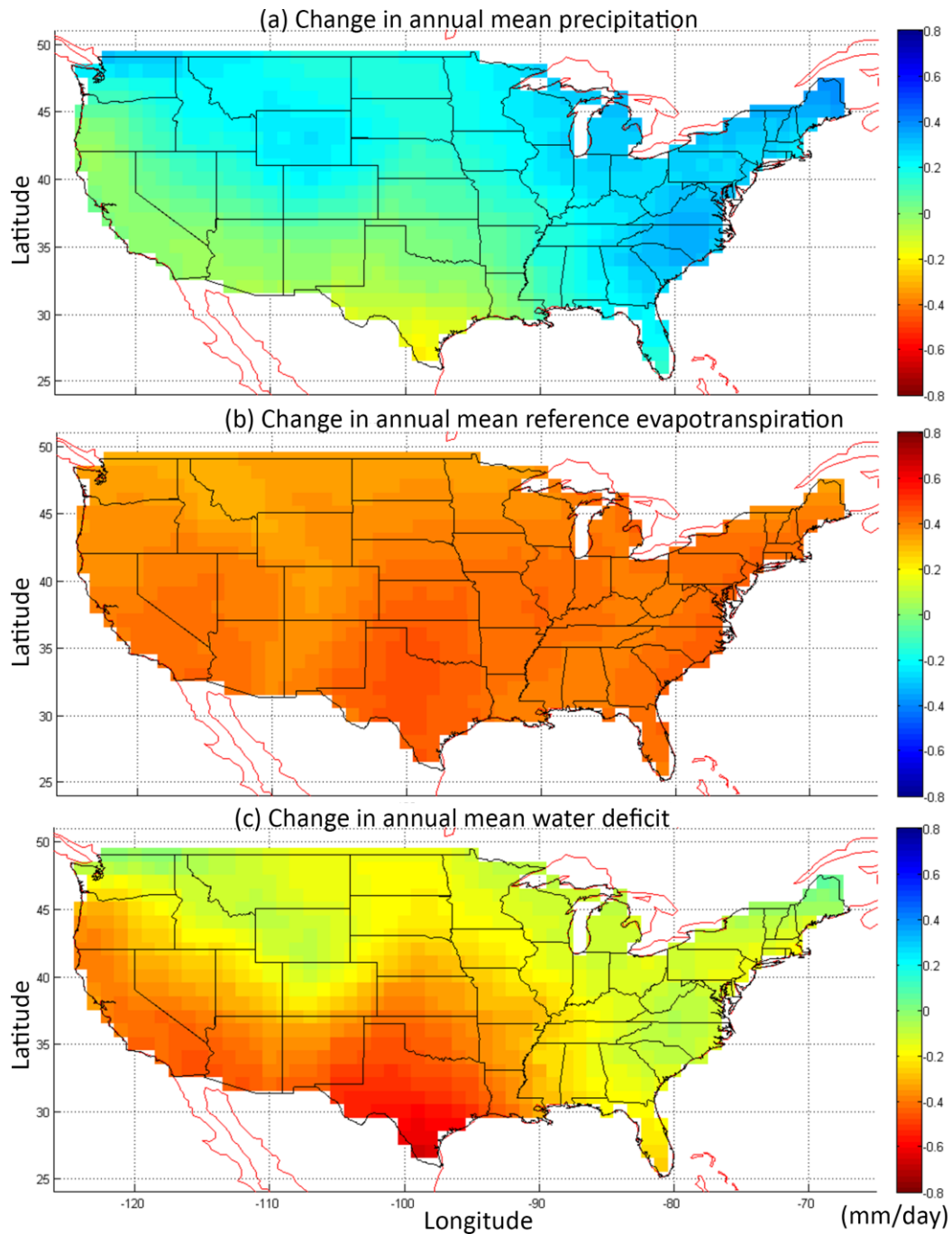
US Climate Regions



653

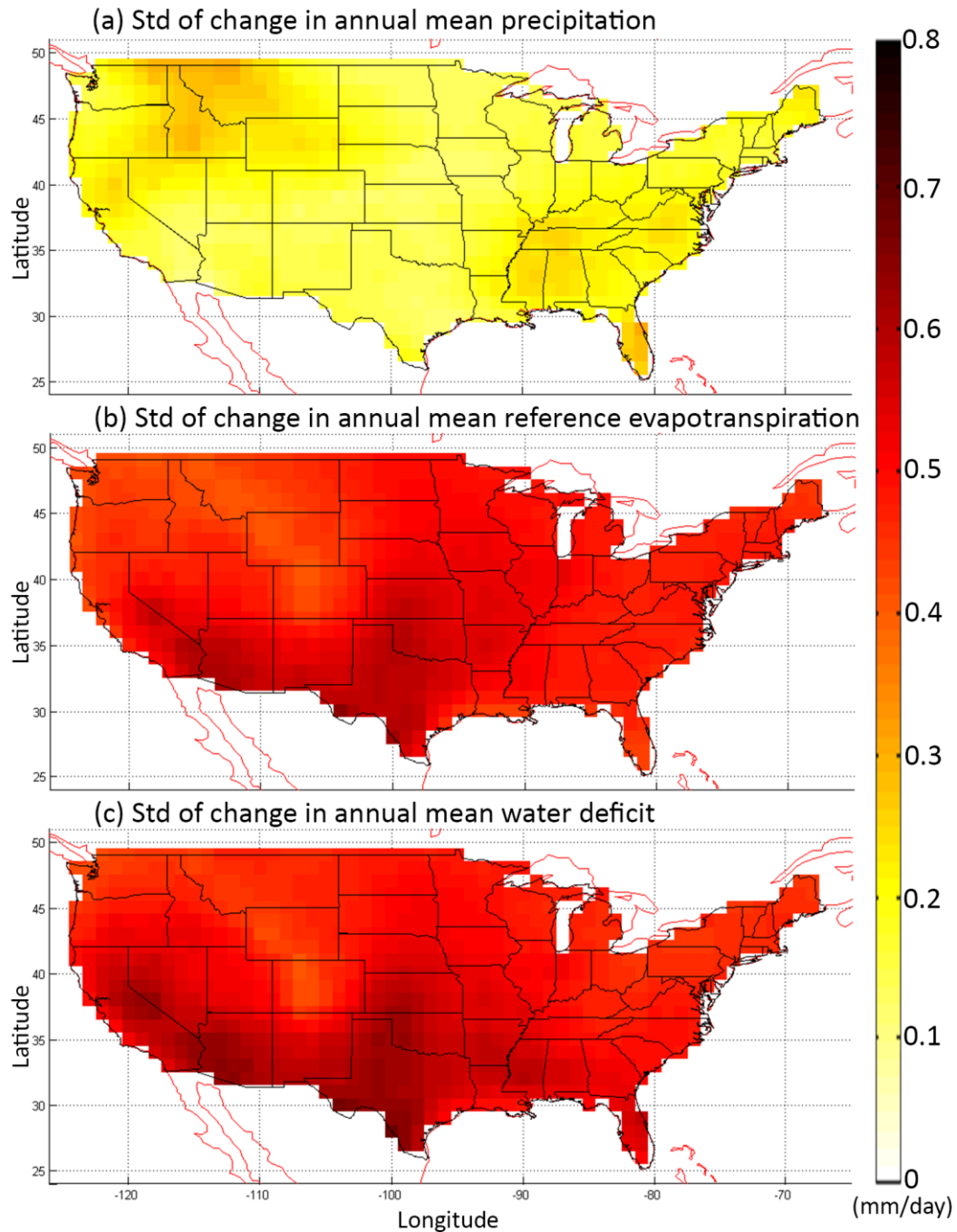
654 Figure 1. US climate regions identified by National Climate Data Center (Adapted from Karl and

655 Koss, 1984, <https://www.ncdc.noaa.gov/monitoring-references/maps/us-climate-regions.php>)



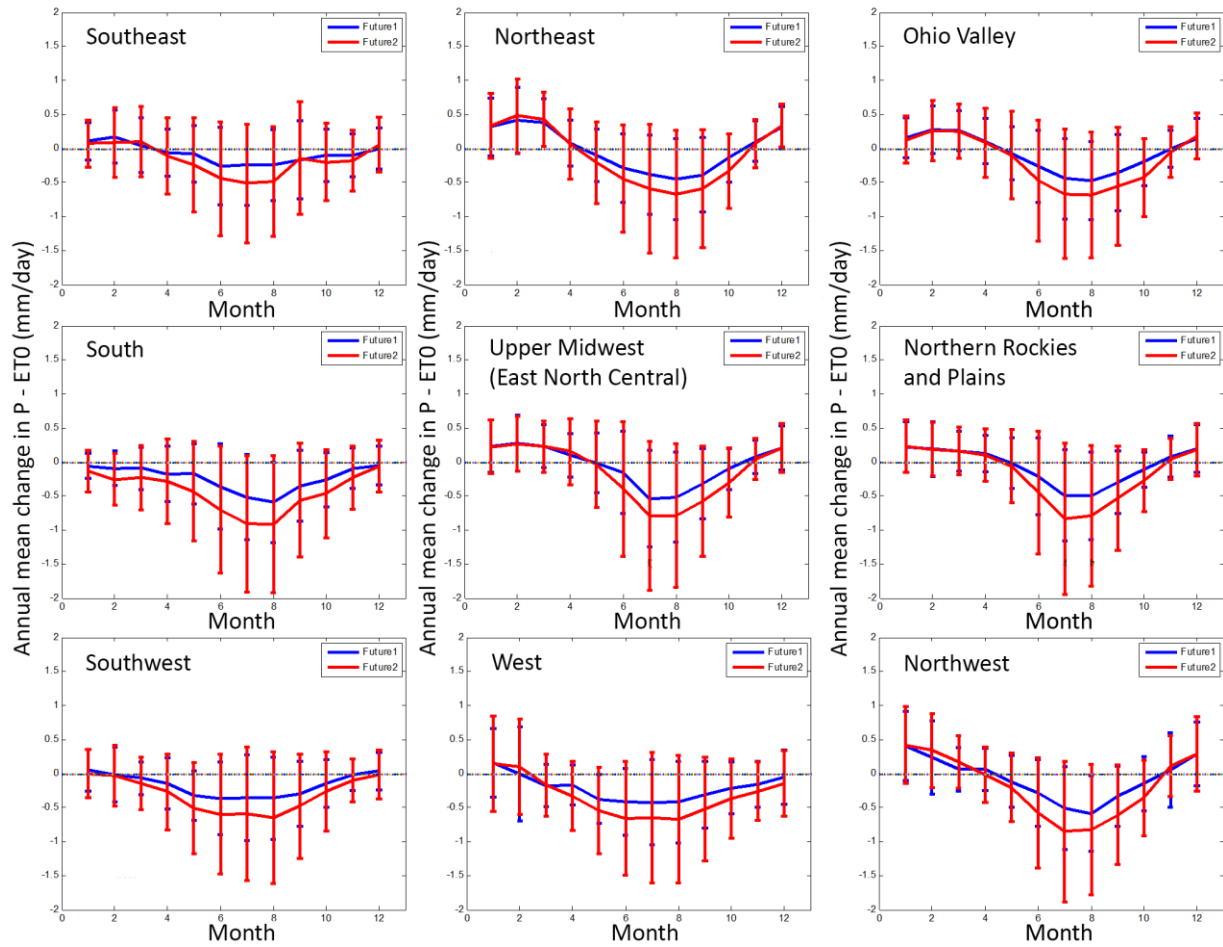
656

657 Figure 2. The change in the annual mean (a) P, (b) ET_0 , and (c) $P - ET_0$ over U.S. All units are
 658 mm/day and the change is defined as the mean of 2070-2100 minus that of 1950-2005. These
 659 changes are averaged over all GCMs, ET_0 estimation methods, and RCP trajectories.



660

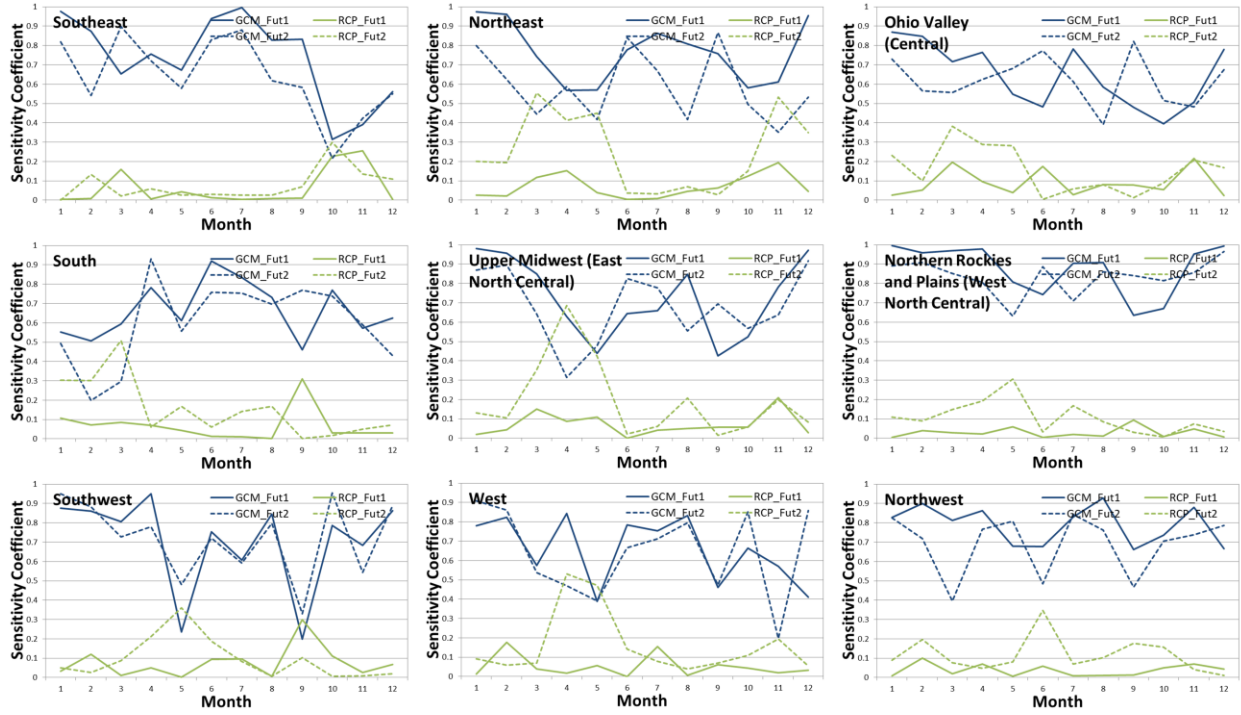
661 Figure 3. The standard deviation of the change in the annual mean (a) P, (b) ET_0 , and (c) $P - ET_0$
 662 over U.S. All units are mm/day and the change is defined as the average of 2070-2100 minus that
 663 of 1950-2005. The standard deviations are estimated over all GCMs, ET_0 estimation methods,
 664 and RCP trajectories.



665

666 Figure 4. The change of monthly mean water deficit ($P - ET_0$) over 9 different regions. Blue
 667 lines represent future 1 period (2030-2060), and red lines represent future 2 period (2070-2100).
 668 Error bars represent one standard deviation of each values. The change is defined as the mean of
 669 future periods minus that of retrospective period (1950-2005).

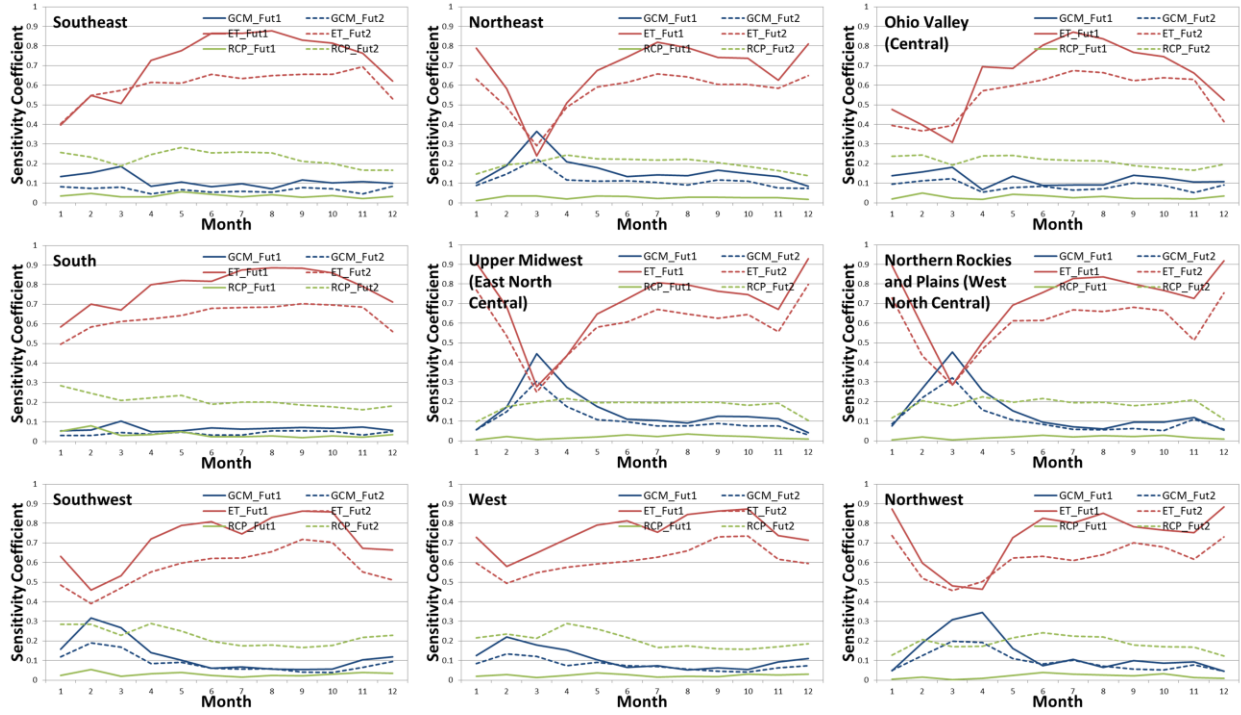
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671

672 Figure 5. First order sensitivity analysis results of change in precipitation. Solid lines represent
 673 the future period 1 (2030-2060) and dotted lines represent the future period 2 (2070-2100). Blue
 674 lines represent the first order effect of GCMs and green lines represent the first order effect of
 675 RCPs.

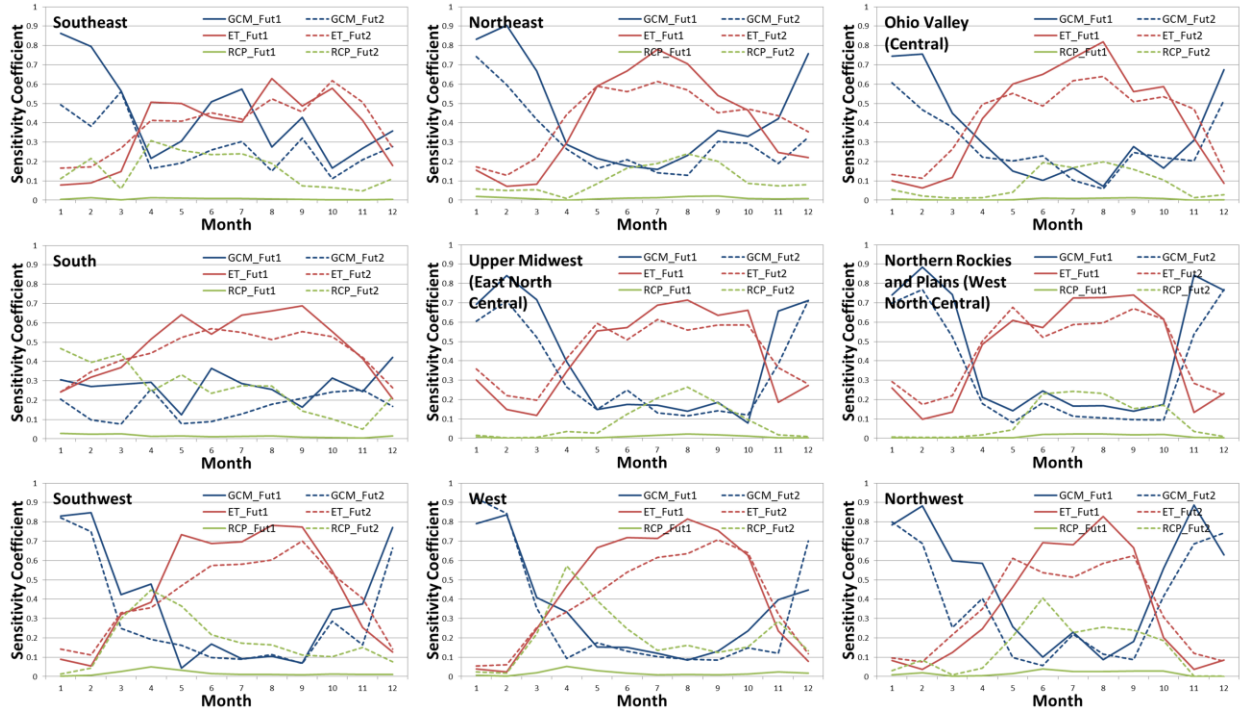
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677

678 Figure 6. First order sensitivity analysis results of change in reference evapotranspiration. Solid
 679 lines represent the future period 1 (2030-2060) and dotted lines represent the future period 2
 680 (2070-2100). Blue lines represent the first order effect of GCMs, red lines represent the first
 681 order effect of ET_0 estimation methods and green lines represent the first order effect of RCPs.

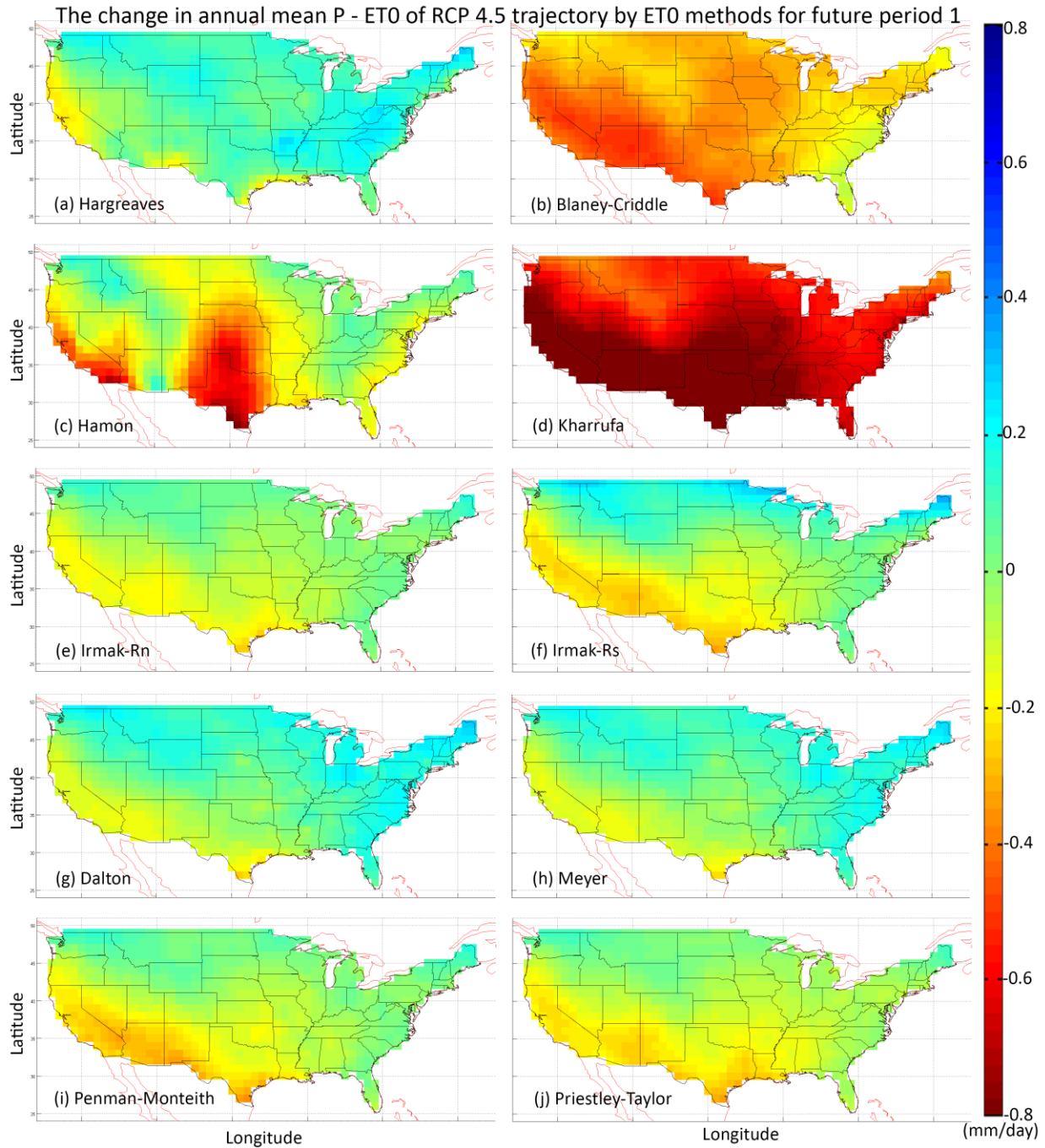
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683

684 Figure 7. First order sensitivity analysis results of change in $P - ET_0$. Solid lines represent the
 685 future period 1 (2030-2060) and dotted lines represent the future period 2 (2070-2100). Blue
 686 lines represent the first order effect of GCMs, red lines represent the first order effect of ET_0
 687 estimation methods and green lines represent the first order effect of RCPs.

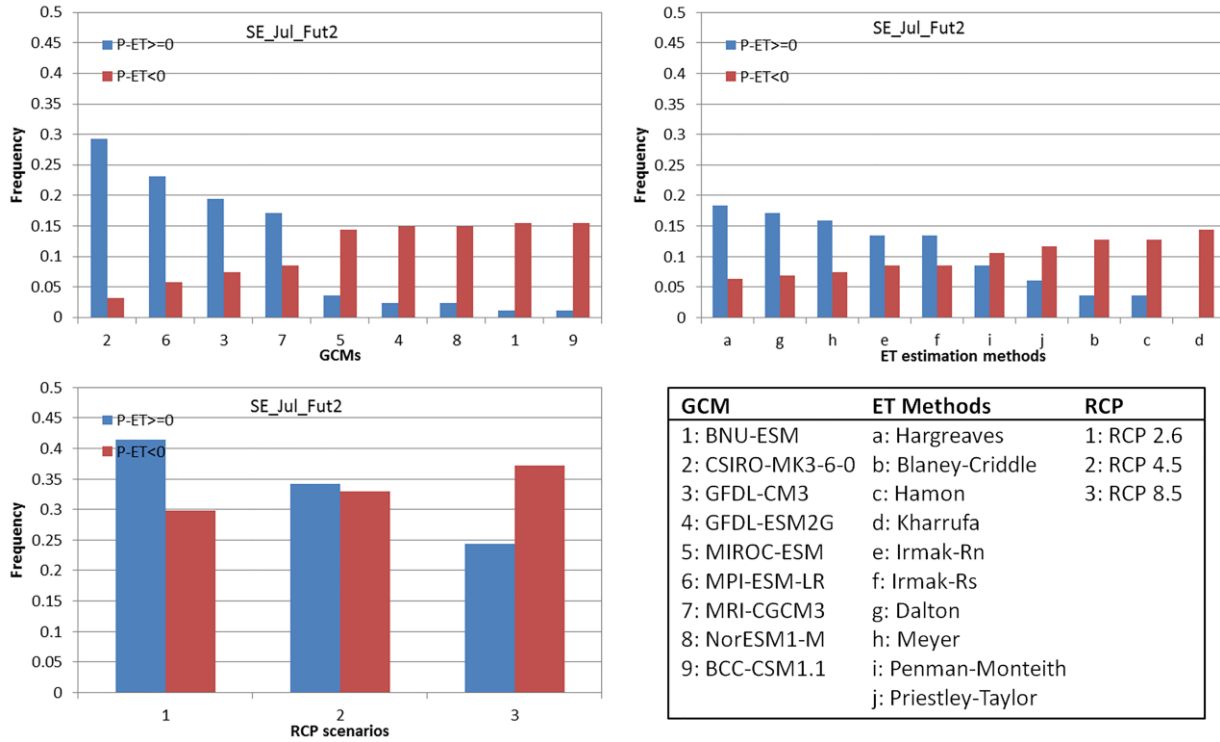
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689

690 **Figure 8.** The change in the annual mean P – ET₀ of RCP 4.5 scenario by 10 different
 691 evapotranspiration methods. All units are mm/day and the change is defined as the mean of
 692 2030-2060 minus that of 1950-2005. (All results are interpolated to 1 degree * 1 degree grids and
 693 averaged over 9 different GCMs)

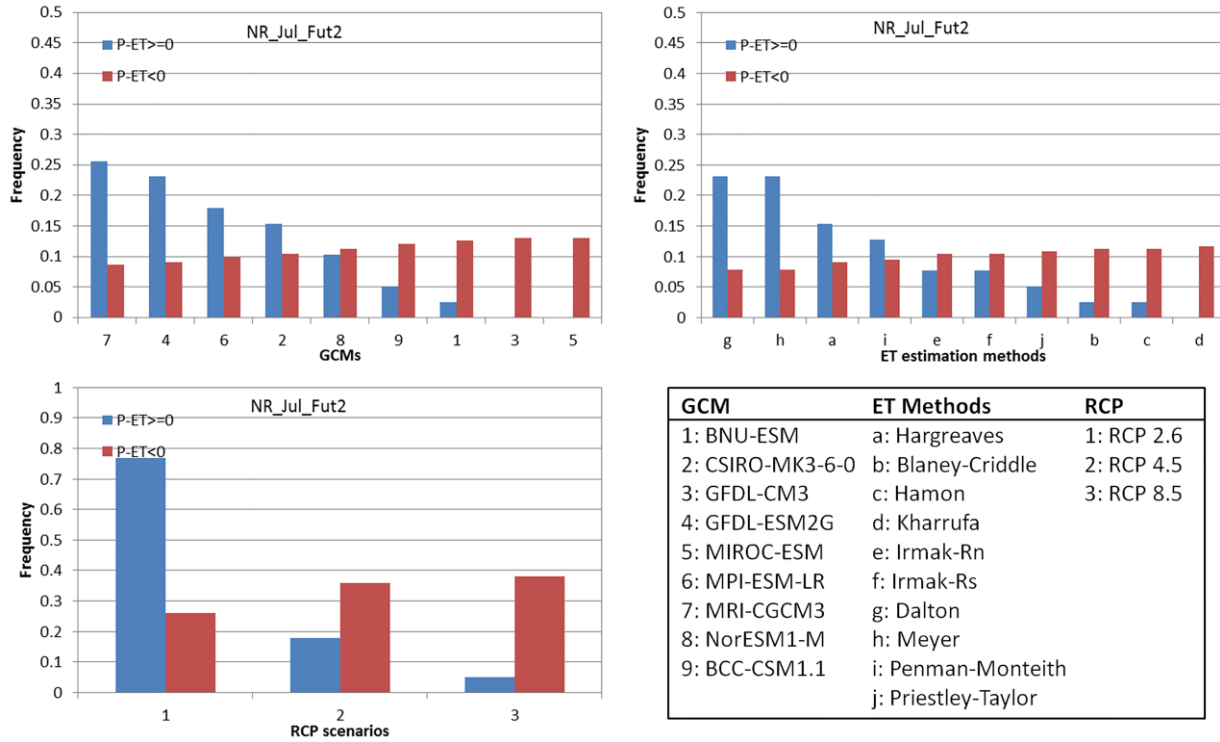
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695

696 Figure 9. Histograms for projected future 2 wet conditions and dry conditions in the Southeast
 697 US by GCM, ET₀ method and RCP trajectory for the month of July.

698

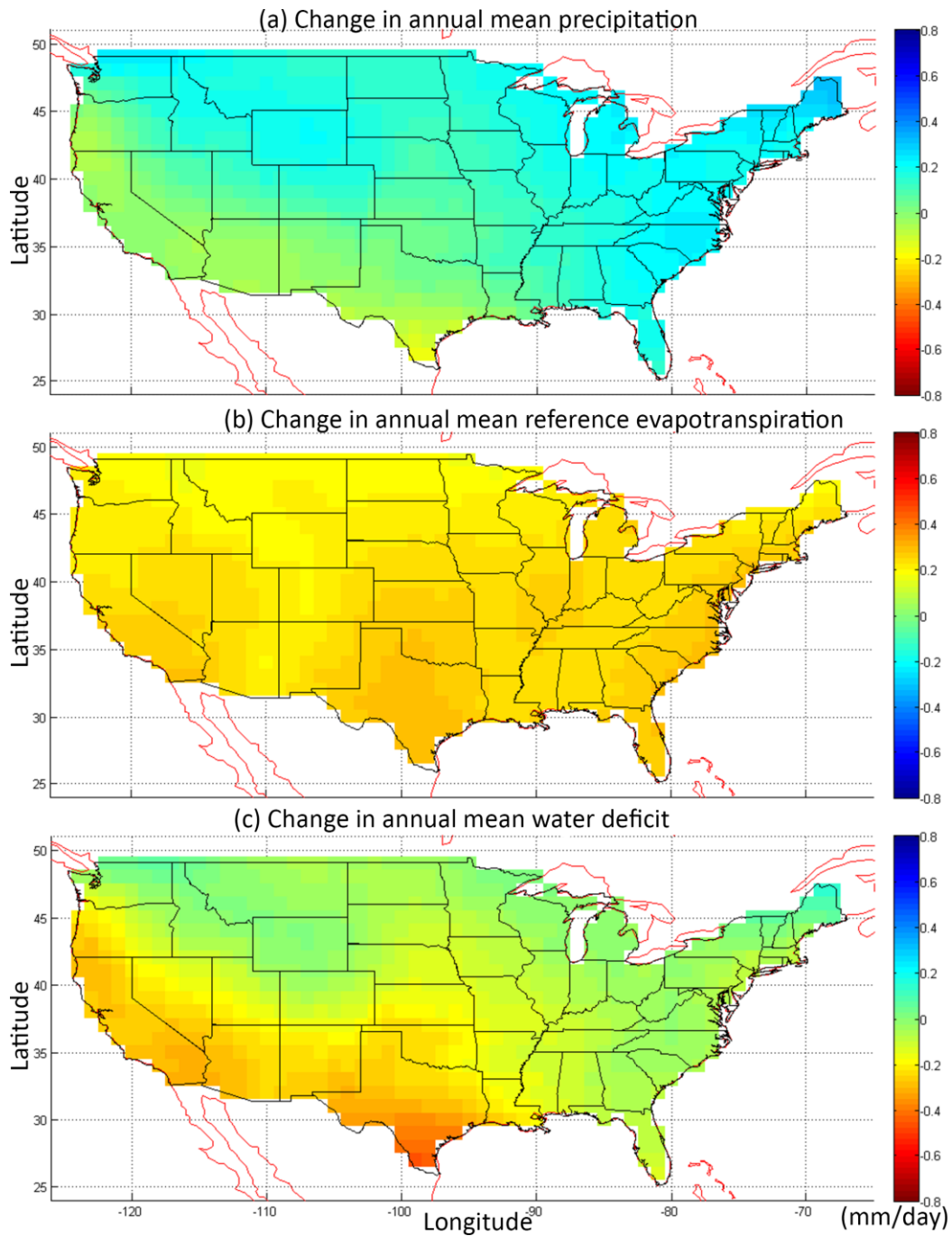


699

700 Figure 10. Histograms for projected future 2 wet conditions and dry conditions in the Northern
 701 Rockies and Plains US by GCM, ET₀ method and RCP trajectory for the month of July.

702

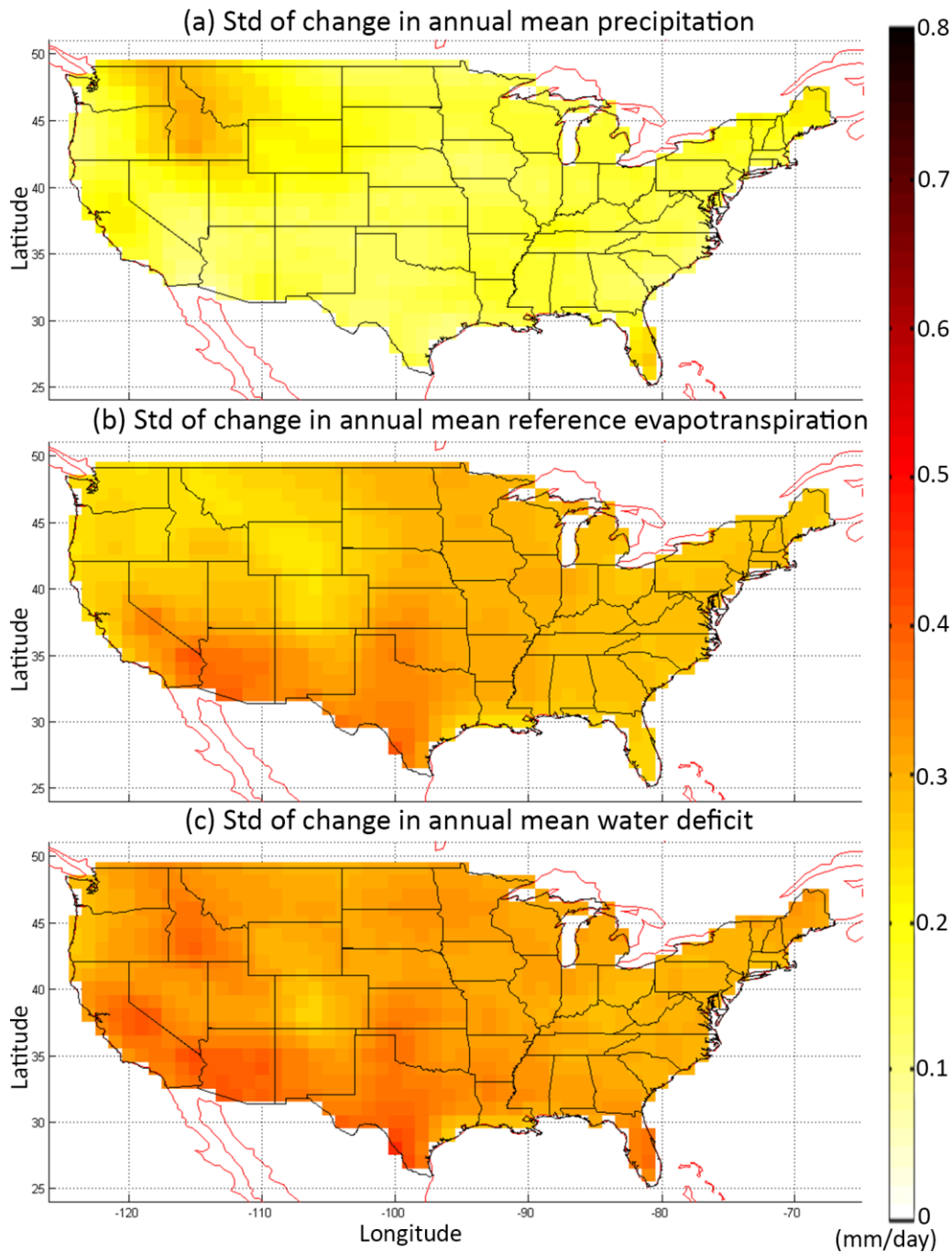
703 **Appendix A: Supplemental figures**



704

705 Fig. S-1 The change in the annual mean (a) P, (b) ET_0 , and (c) $P - ET_0$ over U.S. All units are
706 mm/day and the trend is defined as the average of 2030-2060 minus that of 1950-2005.

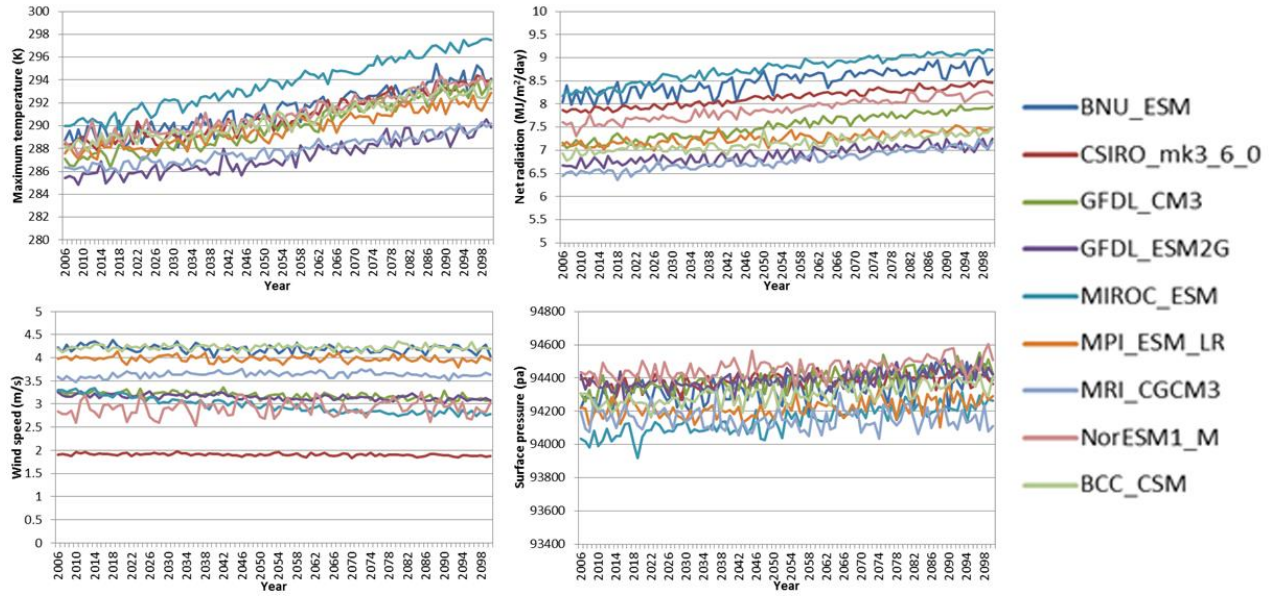
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708

709 Fig. S-2 The standard deviation of the change in the annual mean (a) P, (b) ET₀, and (c) P - ET₀
 710 over U.S. All units are mm/day and the trend is defined as the average of 2030-2060 minus that
 711 of 1950-2005.

712



713

714 Fig. S-3 Mean maximum temperature, net radiation, wind speed at 2 m surface, and surface
 715 pressure of CMIP5 for future period (RCP 8.5).

716