Anonymous Referee #1

We are grateful to the reviewer for the thoughtful and detailed comments. Here we present our response to the comments and plan of revision.

Reviewer comment

In this manuscript, Duan et al. evaluated the relative importance of climate variables (precipitation, temperature, humidity, wind speed and solar radiation) in changing the annual runoff volume under future climate change scenarios in the United States. They apply an ecohydrological model on a monthly basis and additionally run the model with two different potential evaporation inputs. Temperature will outweight the historic importance of precipitation for runoff variability in the future in most of the U.S. although increased humidity can partly reduce evaporative demand and therefore lead to an increase in runoff. The way potential evaporation is calculated has an effect on runoff simulations, but using a variety of climate variables is considered as a more important factor in climate studies.

This is an interesting study and I like the clear and well described concept. The results are illustrated and described in detail for different levels of spatial aggregations and clearly support the conclusions. The main limitations as well as the implications of the study are well discussed. To further improve the manuscript, I have some suggestions listed below including the combination of some of the tables and figures to condense the information and evaluating the results based on hydroclimatic regions. I hope that the comments below will be helpful for the authors to improve their manuscript.

P2 Abstract: I think the abstract would benefit from some more precise or detailed information. E.g. L3: name of the model and simulated time resolution (month); L13-16: It is stated that precipitation will lead to an increase in runoff, while for temperature it only states that there is a large effect but does not explicitly say in which direction (increase or decrease). L18-19: Why do the Midwest and South-Central regions have a severe runoff depletion?

Author reply

We will clarify these issues in the revised abstract.

Reviewer comment

P5 L16-18: This comment is about the WaSSi model: a) What are the benefits of using the WaSSI model and not a simpler model (e.g. a model with less input data and probably less parameters) in your study? b) Snow routine and the ET model are well described. Could you also give some more information about the structure of the SAC-SMA model? A schematic of the WaSSi model could help the reader to more easily understand the model structure, its disaggregation into land cover types, number of parameters, etc. c) Does each catchment (HUC 8 level) have only one single parameter set which is used for runoff simulations and why? Using many more parameter sets could make the results more robust and reliable.

Author reply

We will add more information about the SAC-SMA model. WaSSI was integrated from a snow model, a ET model, and SAC-SMA model. It was specifically developed to capture large-scale water balance in the conterminous US based on empirical and physically based parameters. The parameters of snow model were calibrated for different HUC-2 regions; the parameters of ET model were calibrated for different HUC-2 regions and land-cover types; the parameters of SAC-SMA model were derived from soil properties at 1×1 km resolution (State Soil Geographic Database, STATSGO). Comparing with other simpler models, such as widely used Budyko equations, users can directly use these tested parameters available for the conterminous US and do not need to go through the processes of parameterization for each single watershed. We agree that uncertainty exists in these parameters, but the accuracy has been proved satisfactory.

Please see the second paragraph of Section 2.1 for a more detailed description of the parameters. Readers are referred to McCabe and Markstrom (2007) for the snow model, Sun et al. (2011) for the ET model, Caldwell et al. (2012) for the structure of WaSSI, and Koren et al. (2003) for the SAC-SMA parameters.

References:

Caldwell, P., Sun, G., McNulty, S., Cohen, E., and Moore Myers, J.: Impacts of impervious cover, water withdrawals, and climate change on river flows in the conterminous US, Hydrology and Earth System Sciences, 16, 2839-2857, 2012.

Koren, V., Smith, M., and Duan, Q.: Use of a priori parameter estimates in the derivation of spatially consistent parameter sets of rainfall-runoff models, Calibration of Watershed Models, 6, AGU, Washington, D.C., 239-254 pp., 2003.

McCabe, G. J., and Markstrom, S. L.: A monthly water-balance model driven by a graphical user interface, Geological Survey (US)2331-1258, 2007.

Sun, G., Caldwell, P., Noormets, A., McNulty, S. G., Cohen, E., Moore Myers, J., Domec, J. C., Treasure, E., Mu, Q., and Xiao, J.: Upscaling key ecosystem functions across the conterminous United States by a water-centric ecosystem model, Journal of Geophysical Research, 116, 10.1029/2010JG001573, 2011.

Reviewer comment

P5 L16-18: Could you maybe say a few words about the selection criteria of your study catchments? E.g. did you use all catchments available in the U.S. at HUC 8 level and is human influence on the study catchments problematic for your results? Please also provide the source of your catchment data (catchment outline, runoff data, etc.) in the text and the references.

Author reply

Yes, we calculated all the 2,099 HUC-8 watersheds in the conterminous US. We will add a section "2.1.1 Study area" to briefly introduce the American hydrologic unit system to international readers.

The hydrological model was validated by discharge in 10 representative watersheds without significant human influence (Caldwell et al., 2012) to make sure that the model reproduces precipitation-runoff processes. In this study, we focused on the potential changes in climatic variables, and did not consider the potential effects of land cover change (e.g., urbanization, forestation) and other human activities (e.g., river regulation and water transfer projects).

Reviewer comment

P8 L12-14: EInt is calculated as the difference between the change in runoff and the combined effect of the climate variables. Doesn't this assume a perfect model, i.e. that the selected variables can explain all the runoff changes?

Author reply

This study was limited to the effects of these changing climatic variables with the assumption that other factors (i.e., soil properties, land cover and land use) remain constant. Thus, the runoff change we presented as 'total' effect was a result of the changing climate only, and this change in runoff was attributed to different climatic variables to compare their relative roles. Runoff response to these changes depends on model structure (mainly sensitivity of PET) and the magnitudes of these changes.

Reviewer comment

P9 L4-6: This sentence lists minimum and maximum temperature as climate variables, but Fig. 3 refers to surface air temperature only. Does Fig. 3 show the mean of the minimum and the maximum temperature? Which temperature was used for runoff simulations?

Author reply

We only showed the general trends of annual mean values in Fig. 3. Monthly averages of daily minimum, maximum, and mean (estimated as the average of min + max) temperature were all used in runoff simulations, and the '*T* effect' represented the effect of changes in all of them. We will clarify this at the end of Section 2.3.2.

Reviewer comment

P14 L20-22; P15 L9-11; P15 L19-22: I strongly recommend to make more explicit references to tables and figures to clearly indicate the reader where to find the described information. E.g. P14 L20-22: Table 2 does not provide information about Sh, Rs and Ws. P15 L9-11 and P15 L19-22: I couldn't find the indicated percentages in Fig. 8 or Table 3.

Author reply

We will rephrase the caption of Table 3 and the references in the manuscript to make it clearer.

In P14, the contributions of Sh, Rs and Ws were derived from their independent effects. We did not add another figure to show the detailed contributions of each climatic variable because their relative contributions are consistent with the magnitudes of independent effects shown in Fig. 4.

In P15, all the areal percentages can be found in Table 3. Note that we marked two kinds of areal proportions in the table to keep it concise. The areas where a variable is the largest driving factor identified by multi-model averages is marked in the brackets (L9). The areas where a variable is identified as the 'dominant' factor are bolded (L11). A climate variable is identified as the 'dominant' one only when 80% or more of the 20 GCMs agree that it will be the largest driving factor of runoff change.

Reviewer comment

P19-P20 Conclusions: Similar to the abstract I would recommend to be more precise. E.g. L17: to what exactly do the large uncertainty and spatial variability refer to? (projected changes in runoff?). L1: what is negatively affected by the increasing temperature? (annual runoff?). L6-7: temperature will decrease runoff. L17: temperature based PET tends to be oversensitive to changes in temperature compared to Penman-Monteith.

Author reply

We will clarify these issues in the revised manuscript.

Reviewer comment

P27 Table 1: Table 1 and Fig. 3 contain to a large degree redundant information. To me it is most important to have an impression of the general trends of the 5 climate variables T, P, Sh, Rs and Ws in the two RCPs while the origin country of a GCM is not relevant for the interpretation of the results. Since Fig. 3 provides the trend information of the climate variables, I recommend to delete Table 1 and list the names of the GCMs in the text of section 2.3.

Author reply

Future changes in precipitation and temperature are the focus of this study, and the results support that these two variables are likely to have larger effects on runoff than other variables. Although we have showed the general trends of climate change in Fig. 3, it is difficult to see the magnitude of changes due to the large uncertainty ranges. Especially for precipitation, it is the most difficult variable to predict yet the most important input for runoff modeling. Our results directly depend on the projections of these GCMs. Therefore, before presenting the results, we want to give readers some idea about the magnitudes of climate change in the US and how different models agree or disagree on it.

Reviewer comment

P31 Fig. 1: I am not sure if these two figures are necessary. Fig. 1a is only used in the context of the WaSSi model, where the individual land cover types are listed. Since the map is not further used in the results or discussion part I probably would remove it. Fig. 1b could maybe also be skipped - WRR names could be added to Table 2 and WRR IDs could be added to the maps of Fig.5 and Fig.8. Having the IDs directly in the maps would support the readability of the results where usually a reference to the WRR is made.

Author reply

We agree that land cover distribution is not essential to the interpretation of this study. We thus will delete Fig. 1a. However, we feel that the figure of WRRs might be necessary, especially for readers who are not familiar with the hydrologic regions in the US. This map can directly display the locations of major rivers and drainage basins. Showing WRR names in a table may make it difficult to match names with locations.

Reviewer comment

P36 Fig. 6: This is a more general comment on the use of WRRs and therefore also applies to Table 2 and the corresponding results parts. I wonder how much the averaged results on the level of WRR actually tell us? WRR can be considered as very large watersheds spanning a wide range of land cover types and hydroclimates. The runoff response of subbasins of a WRR to changes in climate variables can therefore be very diverse, which can be seen in Fig. 8. From a hydrological perspective it would be interesting to see exactly these relationships between changes in runoff response and hydroclimate, land cover, etc. Averaging the runoff response over a WRR makes conclusions about possible relationships difficult. In my opinion it would be worth to analyze the runoff response to changes in P and T in dependence of the hydroclimate (e.g. see studies of Coopersmith et al., 2014; Sawicz et al., 2014) or the Köppen Geiger climate zones.

Author reply

We agree it is an interesting issue worthy of further investigation. As a matter of fact, we indeed have tried to sort the results by aridity (the ratio of precipitation to potential evapotranspiration) and land cover types across the country, but unfortunately we could not find any particular pattern due to the large uncertainty in the magnitudes of climate change. We followed the common practice to present results by WRRs, which could provide some useful information for water resources managers and stakeholders.

Reviewer comment

P38 Fig. 8: The information of Table 3 and Fig. 8 is very similar. Is it possible to combine the two? The fact that solar radiation, wind speed and specific humidity have little effect on changes in runoff response is already illustrated in Fig. 7 and therefore does not need to be repeated in Table 3. The areal proportions for precipitation and temperature as driving factors could be directly added to the maps in Fig. 8.

Author reply

Table 3 is a summary of Fig. 5 (mean runoff change) and Fig. 8 (relative role of precipitation and temperature). We tried to display that runoff in precipitation-dominated watersheds are more likely to increase due to the widespread increase in both precipitation and humidity, while runoff in temperature-dominated watersheds may either increase (the combined effects of other factors exceed the temperature effect) or decrease (temperature effect exceeds the combined effects of all the other factors). Since the spatial patterns in Fig. 5 and Fig. 8 are different, putting everything in Fig. 8 might be confusing and misleading. However, we agree that Table 3 can be simplified. We will rephrase the caption and delete the results of radiation and wind (all zero).

Reviewer comment

P8 L3-16: The terms "climate variables" and "driving factors" are used interchangeably as synonyms, which can be confusing. I recommend to use only one of the two terms.

P8 L7-8: I recommend to write ": : :independent effects E of each driving factor Ci..."

P8 L15: Based on equation 3 I assume that the contributions of the climate variables are quantified by the absolute relative weights.

Author reply

We will rephrase this section according to the reviewers' comments.

Reviewer comment

P9 L13-19: The first two sentences about sensitivity are to my perception not so relevant and could be deleted. I don't fully understand the last sentence - does pooling mean averaging of results?

Author reply

These two sentences are meant to briefly explain why we used this approach and why it is more robust for examining the long-term patterns in an uncertain future. It might provide some useful information for readers who are interested in the method.

"Pooled" will be changed to "collected".

Reviewer comment

P11 L2: I would not use abbreviations in the title.

Author reply

We will change the acronyms in titles to the actual words.

Reviewer comment

P20 L7-9: I think it is not necessary to mention in the conclusion that the Midwest has vast areas of croplands and grasslands, because this was not a major finding of the study.

Author reply

We will delete this sentence from the Conclusions.

Reviewer comment

P32 Fig. 2: The R-square values mentioned at P7 L16 could be added to the graph.

Author reply

We will add it.

Reviewer comment

P36 Fig. 6: The figure caption explains the elements of a boxplot. If you think this is needed you should also add the explanation in Fig. 7 to be consistent. Additionally, I recommend to use the same y-axis labels in the two figures.

Author reply

We will add a statement in the caption of Fig. 7: "The format of the box-whisker plots is the same as that in Figure 6". The y-axis in Fig. 6 and Fig. 7 was set different because the variations at regional scale (Fig. 6) are clearly larger than that at CONUS scale (Fig. 7).

Reviewer comment

Please use the HESS guidelines for all abbreviations and units. E.g. P33 Fig. 3: adapt units from W/m2 to W m-2.

Author reply

It will be fixed.

Reviewer comment

According to the HESS guidelines, authors are encouraged to briefly describe the contribution of each co-author in a section called "author contributions".

Author reply

It will be added.

Reviewer#2 - Finlayson

Reviewer comment

The overall academic content of this paper is sound, exploring the possible future runoff across the coterminous United States under conditions that may develop as predicted global climate changes unfold. However, my concerns with this paper relate to the way this material is presented. The authors appear to be unaware that they are writing to a global audience, and not to a group who, like themselves, are very familiar with the geography of the coterminous USA and with the systems used for identifying watersheds and location in the USA. I list below a series of points to illustrate my concerns.

Author reply

We thank Dr. Finlayson for pointing out this important issue. We will add a section of "Study area" at the beginning of "2 Mehtods" to introduce the American hydrologic unit system and clarify the object of this study. The descriptions involving the geography of the conterminous US will be revised through the manuscript. Point-by-point responses are listed below.

Reviewer comment

P 1 Lines 5-6: The use of the phrase "hydrologic paradigms" seems inappropriate here.
What is at issue here is the strength or intensity of different hydrological processes. Paradigms are something rather different.

Author reply

We will change it to 'water balance', which is a more general term and may be more appropriate here.

Reviewer comment

P 1 Line 7: "intensification of hydrologic cycle". What does this phrase mean?

Author reply

We referred to the phenomenon that climate warming causes general increases in evaporation and precipitation, and higher frequency of extreme hydrologic events, which indicates an intensification (or acceleration) of the water cycle (Huntington, 2006).

Huntington, Thomas G. "Evidence for intensification of the global water cycle: review and synthesis." Journal of Hydrology 319.1 (2006): 83-95.

Reviewer comment

P 1 Line 12: The use of "sustainably" in this context seems rather out of place. There are a lot of surface water sources and shallow aquifers that are being used very unsustainably.

Author reply

This sentence will be revised to "runoff is a critical source of fresh water for humans".

Reviewer comment

P 4 Lines 16-17 "the rate of decadal change of temperature over the CONUS has reached -0.03~+0.28 °C since 1960s". I'm not sure what this means, it needs to be more clearly stated.

Author reply

This sentence will be revised to "the rate of decadal change in temperature over the CONUS fluctuated between -0.03 °C and +0.28 °C from 1960s to 2000s".

Reviewer comment

The authors assume that the readers have an intimate knowledge of some of the materials they are working with. So, for example, they use the term "8-digit Hydrologic Unit Code (HUC-8) watersheds" and "2-digit HUC Watershed". I have no idea what these are and I suspect I'm not the only one. The paper needs to be written for an international audience and not a just a group of those specialising in North American hydrology.

Author reply

We will add a section "2.2.1 Study area" to clarify the object of this study and introduce the American hydrologic unit system.

Reviewer comment

P 8 I do not follow the discussion from Line 3 to Line 17. Especially this term (Line 12) - R(C1t1,…,Ci t2 ,…,CNt1) - R(C1t1,…,Ci t1,…,CNt1). What is going on here needs to be explained more clearly, or is there a misprint?

Author reply

$R(C1_{t1},\ldots,Ci_{t1},\ldots,CN_{t1})$ denotes runoff under the climate condition in the time period of $t1$. $R(C1_{t1},\ldots,Ci_{t2},\ldots,CN_{t1}) - R(C1_{t1},\ldots,Ci_{t1},\ldots,CN_{t1})$ denote runoff change driven by the change in variable Ci from $t1$ to $t2$, while other variables remain constant.

We will rephrase this section according to reviewers' comments.

Reviewer comment

P 8 Line 20 "statistically downscaled" What does this mean? Is this a way of saying that the means or the medians were used?

Author reply

We were trying to say that the data was corrected and downscaled from raw climate model outputs using statistical downscaling methods. This sentence will be broken into shorter sentences to avoid confusion.

Reviewer comment

P 9 lines 1-2 "RCP4.5 and RCP8.5 were adopted as representatives of the intermediate and high emission scenarios respectively". At this point in the paper the readers have no idea what RCP4.5 and RCP8.5 are. There is some explanation later in the paragraph but it is not particularly clear. These terms need to be defined before they are used.

Author reply

We will rewrite this paragraph to clarify the datasets and scenarios used in this study.

Reviewer comment

Similarly, in Section 3, where the results are presented, Water Resource Regions (WRR) are referred to by their numbers and sometimes also the name of a general region, such as Midwest, Mountain West or coastal regions, in this case with no indication which bits of the coastal US are being referred to.

Author reply

In the revised version, we will avoid terms that are not familiar to international audience, such as ‘Midwest’ and ‘Mountain West’. We will use more general descriptions such as ‘central U.S.’ and ‘northwest of U.S.’.

In P14 L9, “coastal regions (WRR1,2,18)” will be revised to “Atlantic coast (WRR1,2) and Pacific coast (WRR18)”.

Reviewer comment

The writing style is rather unsatisfactory with frequent lack of the definite article and missing and incorrect words. Here is an example: “For example, slight decreases in P but somewhat increases in R are projected in south Texas due to the alteration of innerannual climate variability.” I suspect that this, and the many similar cases in the text, come about from reviewing the text using the word processor’s spelling check rather than careful reading by the authors.

Author reply

We will recheck the writing more carefully based on the reviewers’ comments.

Reviewer comment

In Section 4.3 the authors argue that the results presented here indicate that “Additional water storage such as reservoirs and flood prevention measures may be needed in regions expecting more R”. That may be the case but there is no evidence in this study that relates to flood behaviour and simply an increase in runoff does not say anything one way or the other about how floods will behave.

Author reply

We will delete the statement about flood.

Future shift of the relative roles of precipitation and temperature in controlling annual runoff in the conterminous United States

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Abstract This study examines the relative roles of climatic variables in altering annual runoff in the conterminous United States (CONUS) in the 21st century, using a~~n~~ monthly ecohydrological model (the Water Supply Stress Index model, WaSSI) driven with historical records and future scenarios constructed from 20 Coupled Model Intercomparison Project Phase 5 (CMIP5) climate models. The results suggest that precipitation has been the primary control of runoff variation during the latest decades, but the role of temperature will outweigh that of precipitation in most regions if future climate change follows the projections of climate models instead of the historical tendencies. Besides these two key factors, increasing air humidity is projected to partially offset the additional evaporative demand caused by warming and consequently enhance runoff. Overall, the projections from 20 climate models suggest a high degree of consistency on the increasing trends in temperature, precipitation, and humidity, which will be the major climatic driving factors accounting for 43%~50%, 20%~24%, and 16%~23% of the runoff change, respectively. Spatially, while temperature rise is recognized as the largest contributor that suppresses runoff in most ~~of the CONUS~~areas, precipitation is expected to be the dominant factor driving runoff to increase across the Pacific Coast and the Southwest. The combined effects of increasing humidity and precipitation may also surpass the detrimental effects of warming and result in a hydrologically wetter future in the East. However, severe runoff depletion is more likely to occur in the ~~Midwest and South Central~~central CONUS as temperature effect prevails.

1 Introduction

Precipitation and temperature are the two key climatic variables that control land water balances and thus control water availability for both ecosystem and humans (Lutz et al., 2014;Milly et al., 2005;Seager et al., 2013;Piao et al., 2010). Changes in temperature interact with changes in precipitation and cause profound shifts in ~~hydrologic paradigms~~water balance, such as snowpack melting and accumulation (Barnett et al., 2005;Zhang et al., 2015), intensification of hydrologic cycle (Creed et al., 2015;Davis et al., 2015), precipitation partitioning (Duan et al., 2016b;Zhou et al., 2015), extreme floods and droughts (Duan et al., 2016a;Trenberth et al., 2014;Duan and Mei, 2014b), and can lead to hydrological 'nonstationarity' (Milly et al., 2008).

Surface and subsurface (shallow aquifers) runoff is a critical source of fresh water ~~that~~ for humans ~~populations sustainably have access to~~ (Vörösmarty et al., 2000). The impacts of temperature and precipitation changes on the magnitude and variability of runoff (Ficklin et al., 2009;Arnell and Gosling, 2013;Nash and Gleick, 1991;Vano et al., 2012) have drawn particular attention due to its importance for water supplies. Future changes in precipitation, evaporation, and plant water use are direct driving forces of runoff generation. Climate change alters both precipitation and the partitioning of precipitation into evapotranspiration (E_{T}) and runoff since a warmer climate generally provides more energy for water fluxes between the land and the atmosphere. Although an increase in precipitation may cause increase in both E_{T} and runoff, the enhanced evaporative demand can result in decreases in runoff efficiency (ratio of runoff to precipitation) (McCabe and Wolock, 2016). Both observation and simulation studies in the U.S. suggest that higher E_T induced by rising temperature is unlikely to be counterbalanced by the increase in precipitation and lead to less runoff at large scales (Duan et al., 2016b;Jackson et al., 2005;Duan et al., 2017). Conversely, warming may also cause precipitation decrease in some regions and exacerbate the effects of temperature on runoff change.

Several studies have examined the relative contributions of historical changes in precipitation and temperature to runoff variation at watershed (Karl and Riebsame, 1989), regional (Ryberg et al., 2014;Gupta et al., 2015), and continental (McCabe and Wolock, 2011) levels across the conterminous U.S. (CONUS). These studies all agree that precipitation, instead of temperature, explains most of the long-term change and variability in runoff during the past century. McCabe and Wolock (2011) suggested that the effects of temperature on runoff may become more substantial under a warming climate. However, no study in the literature has rigorously investigated the potential changes in the roles of precipitation and temperature under future climate scenarios. According to the Parameter-elevation Relationships on Independent Slopes Model (PRISM) dataset (http://prism.oregonstate.edu/) (Daly et al., 2008), the rate of decadal change in~~of~~ temperature over the CONUS ~~has reached~~ fluctuated between -0.03 °C and~~ ~ ~~ +0.28 °C from~~since~~ 1960s to 2000s. The rate of warming is likely to accelerate under intermediate or high emission scenarios and increase the pressure of water scarcity in many regions in this century (IPCC, 2014;Schewe et al., 2014). In addition, future change in climate is projected to vary spatiotemporally in both direction and magnitude in the CONUS (Mearns et al., 2012), thus sensitivity of water budget to climate change may be discrepant across time and space. Although the possible underestimation of the influence of temperature in altering regional water resources has been discussed recently (Sospedra‐Alfonso et al., 2015;Woodhouse et al., 2016), a comprehensive evaluation under different climate backgrounds and land-cover compositions is still lacking.

We aim to address two questions in this study: (1) to what extent, if any, will the relative roles of precipitation and temperature in controlling runoff shift, if future climate changes follow the projections of climate models~~,~~ instead of the tendencies documented in the recent decades, and (2) how will runoff change in the future and what are the potential roles of other climatic driving forces besides precipitation and temperature? In the remainder of the paper, we first describe the methodology of runoff simulation and sensitivity assessment, and the hydro-climatic datasets used, followed by the results. Then, the advantages, limitations, and implications of this study are discussed and the conclusions are drawn.

2 Methods

~~2.1 Runoff modeling~~2.1 Study area

The CONUS covers the 48 adjoining states and the District of Columbia. In the hydrologic unit system developed by the U.S. Geological Survey (USGS) (http://water.usgs.gov/GIS/huc.html), the nation is divided into six levels of hydrologic units and each unit is identified by a unique hydrologic unit code (HUC) consisting of two to twelve digits. The first level of classification divides the CONUS into 18 2-digit HUC areas that are also commonly referred to as Water Resource Regions (WRRs) (Fig.

1). These regions can be further divided into 2,099 8-digit HUC areas, or HUC-8 watersheds. This study investigates climate and runoff variations at the resolution of HUC-8 watershed, as well as the aggregations in each WRR and the entire CONUS. The full lists and boundaries of hydrologic units at different levels can be found in the Watershed Boundary Dataset (https://datagateway.nrcs.usda.gov/).

2.2 Runoff modeling

The runoff responses to climate change and variability ~~are~~ were modeled with the Water Supply Stress Index model (WaSSI)~~ for 2,099 8-digit Hydrologic Unit Code (HUC-8) watersheds (http://water.usgs.gov/GIS/huc.html) across the CONUS~~. WaSSI is a monthly~~water-centric~~ ecohydrological model that simulates the land-cover specific water and carbon cycles ~~on a monthly basis~~ (Caldwell et al., 2012;Sun et al., 2011b). The model incorporates several mathematical sub-models to describe monthly hydrologic processes from precipitation input to streamflow routing. A conceptual snow sub-model (McCabe and Markstrom, 2007) is used to partition the total precipitation into rainfall and snowfall, and to estimate snowpack melt/accumulation and snow water equivalent with concern of the mean elevation, latitude, and air temperature in the watershed. E_{T} is calculated with an ecosystem E_{T} model developed from the empirical relationships between E_{T} and precipitation, potential evapotranspiration (PET), and leaf area index (LAI) (Sun et al., 2011a;Sun et al., 2011b). These E_{T} functions were established for 10 different land-cover classes independently to account for the different water demand within different vegetation, ranging from cropland, deciduous forest, evergreen forest, mixed forest, grassland, shrubland, wetland, open water, urban area, to barren land. Then, this E_T estimation is further constrained by soil water availability, which is simulated using the algorithms of Sacramento Soil Moisture Accounting model (SAC-SMA) (Burnash, 1995), as well as the processes of infiltration and runoff generation at monthly basis. SAC-SMA is a classic rainfall-runoff conceptual model that has been successfully used by the U.S. National Weather Service (NWS) to issue river forecasts across the country for decades.

Necessary inputs for WaSSI include monthly precipitation, air temperature, PET, LAI, and land-cover composition. In this study, the spatial distribution of LAI and the 10 land-cover classes ~~(Fig. 1a)~~ were assumed to be static over time. Monthly climate data were first scaled to watersheds by the area-weighted averages. All the water balance components were calculated independently for each land cover class within each watershed, and then were aggregated monthly means. The model parameters were acquired from several previous studies, including: (1) The parameters of snow sub-model were estimated for each WRR ~~Water Resource Region (WRR, i.e., 2-digit HUC watershed) (Fig. 1b)~~ by comparing regional monthly mean snow water equivalent to remotely sensed values from the Snow Data Assimilation System (McCabe and Markstrom, 2007;Caldwell et al., 2012). (2) The parameters of E_T sub-model were estimated by empirical relationships derived from eddy covariance or sapflow measurements at multiple sites (Sun et al., 2011a;Sun et al., 2011b). (3) SAC-SMA parameters used to drive the soil water balance sub-model were developed from soil physical characteristics documented by the State Soil Geographic Database (http://soildatamart.nrcs.usda.gov) (Anderson et al., 2006;Koren et al., 2003).

The WaSSI model has been validated against observations at ~~U.S. Geological Survey (USGS)~~ USGS gauged sites at the levels of both 8-digit (Caldwell et al., 2012) and 12-digit HUC watersheds (Sun et al., 2015b). We here verify the model performance at CONUS and WRR ~~and continental~~ scales to complement to previous validations. The simulated annual runoff, driven by monthly precipitation and temperature from the PRISM dataset, was compared against the USGS measurements over the entire CONUS (Fig. 2a&2c) and in the 18 WRRs (Fig. 2b&2d) for the time period of 1961-2010. Despite a slight overestimation of the minimums, WaSSI shows reliable accuracy in capturing annual runoff at both CONUS and WRR scales, with R-square statistic reaching 0.91 and 0.95, and Root Mean Squared Error (RMSE) limited to 29 and 55 mm yr^{-1}, respectively.

2.~~2~~3 Quantifying the independent effects of climatic variables

Large-scale water balance can be described as runoff (R) equals precipitation (P) minus E_T and changes in soil moisture (S_M) and the hydrologically connected snowpack (S_P):

$$R = P - E_T + \mathrm{d}S_M/\mathrm{d}t + \mathrm{d}S_P/\mathrm{d}t \quad (1)$$

While P is the primary water input, changing temperature (T) and other climatic factors interact with each other and affects R by altering the melt/accumulation of snowpack and controlling E_T with the constraints of vegetation and soil moisture.

Here we developed a simple approach of sensitivity test to examine the relative roles of climatic variables in R variation, as:

$$\Delta R = \sum_{i=1}^{N} E_{Ci} + E_{Int} \quad (2)$$

where ΔR denotes the change in R, which equals the combined effect~~s~~ of variations in all the climatic variables (C_i, $i=1,2,\ldots,N$). ΔR can be decomposed into the independent effects of each ~~driving factor~~variable (E_{Ci}) and the effect of interactions among them~~ese variables~~ (E_{Int}). From a pre-change period (t_1) to a post-change period (t_2), ΔR is quantified by R change (%)~~ from pre-change period (t_1) to post-change period (t_2)~~ driven by changes in all the ~~factors~~variables, as the difference between $R(C1_{t2},\ldots,Ci\cancel{2}_{t2},\ldots,CN_{t2})$ and ~~−~~$R(C1_{t1},\ldots,Ci\cancel{2}_{t1},\ldots,CN_{t1})$; while E_{Ci} is estimated by R change driven by changes in the variable Ci only, as the difference between $R(C1_{t1},\ldots,Ci_{t2},\ldots,CN_{t1})$ and~~−~~ $R(C1_{t1},\ldots,Ci_{t1},\ldots,CN_{t1})$. E_{Int} is calculated as the ~~difference between~~ ΔR minus~~and~~ $\sum_{i=1}^{N} E_{Ci}$, representing the changes in R that cannot be accounted for by the independents effects. Given that the ~~driving factors~~changing climatic variables may cause either positive or negative effects on R, their contributions (%) are quantified by the relative weights, as

$$C(Ci) = 100 \times |E_{Ci}| / \left(\sum_{i=1}^{N} |E_{Ci}| + |E_{Int}|\right) \quad (3)$$

2.~~3~~ 4 Modeling experiments

2.~~3~~4.1 Climate projection

Climate data ~~projections statistically~~ downscaled from the raw outputs of 20 Global Climate Models (GCMs) (Table 1) of the fifth phase of the Coupled Model Inter-comparison Project (CMIP5) ~~for both historical forcings and future Representative Concentration Pathways (RCPs)~~ (the MACAv2-LIVNEH dataset, Livneh et al., 2013, available at http://maca.northwestknowledge.net/) were used to test the potential future changes in R. This dataset includes the CMIP5 experiments of 'historical', Representative Concentration Pathways (RCP) 4.5, and RCP8.5, which correspond to the climate forcings (i.e., greenhouse gases emissions, aerosols, land use feedbacks, etc.)

observed in the history and projected in a future with the radiative forcing reaching 4.5 and 8.5 W m^{-2} in 2100 (equivalent to 650 ppm and 1370 ppm CO_2), respectively ~~RCP4.5 and RCP8.5 were adopted as representatives of the intermediate and high emission scenarios respectively, which correspond to radiative forcing of approximately 4.5 W m^{-2} and 8.5 W m^{-2} in 2100 (equivalent to 650 ppm and 1370 ppm CO_2)~~ (Moss et al., 2010;IPCC, 2014). The used climatic variables include monthly *P*, maximum and minimum *T*, solar radiation (*Rs*), wind speed (*Ws*), and specific humidity (*Sh*) spanning from 1950 to 2099 (Fig. 3).

To evaluate the *R* responses to various changes in future climates, we conducted four 30-year simulation experiments: (i) RCP4.5/2030s (S1 scenario) — near future 2020-2049 under RCP4.5; (ii) RCP4.5/2080s (S2) — far future 2070-2099 under RCP4.5; (iii) RCP8.5/2030s (S3) — near future 2020-2049 under RCP8.5; (iv) RCP8.5/2080s (S4) — far future 2070-2099 under RCP8.5. These four future scenarios cover two post-change time periods (2030s and 2080s) and are compared to the historical condition in ~~a pre-change period of~~ 1970-1999 (1980s) that represents the baseline level. Traditional sensitivity test methods usually assume a fixed amount of change (Karl and Riebsame, 1989) or allow one (or more) of the variables to remain constant over time (McCabe and Wolock, 2011). In this study, the 30-year-long continuous climate series were used to examine the long-term patterns while implicitly incorporating the inter- and intra-annual variations. This large set of climate projections was collected~~pooled~~ to enable a robust quantification of the major uncertainties from GCM structure and emission scenario.

2.~~3~~4.2 Estimation of potential evapotranspiration~~PET estimation~~

Hamon's PET equation has been used for PET estimation in previous WaSSI simulations because it only requires mean temperature as input and has shown reliable correlation with actual E_T in historical periods (Lu et al., 2005;Vörösmarty et al., 1998). Essentially, temperature-based methods perform well because T is correlated with radiation and humidity at monthly timescale (Sheffield et al., 2012). Such correlations are the physical bases of the empirical E_T functions, through which variability in P, T, and LAI was able to explain the main controls of evaporation and transpiration fluxes without including the radiative and aerodynamic variables. However, recent studies revealed that the bias in temperature-based methods could be amplified in future scenarios of global warming, ~~and led~~leading to overestimation of PET~~,~~ and ultimately E_T and the severity of land surface drying (Milly and Dunne, 2011;Sheffield et al., 2012). Penman-Monteith (PM) reference E_T (Allen et al., 1998), as a commonly used alternative PET model, incorporates the effects of surface temperature, humidity, wind, and radiation, and is considered the most reliable PET approach where sufficient meteorological data exist (Kingston et al., 2009;Feng and Fu, 2013).

In this case, using Hamon equation would lead to 130 mm yr^{-1} larger PET increase from the baseline to RCP8.5/2080s than that using PM equation (Fig. 4). We assume that the PM PET projections are more reasonable because the effects of future changes in *Rs*, *Ws*, and *Sh* are included as well as *T*. In the remaining of this paper, w~~W~~e will focus on analyzing the *R* changes and the independent effects of five climatic variables based on PM PET, ~~(~~i.e., *P*, *T*~~,~~ (including changes in maximum *T*, minimum *T*, and mean *T* that was estimated as the average of maximum and minimum), *Rs*, *Ws*, and *Sh*~~)~~ ~~based on PM PET in the remaining of this paper~~. Effects of *P* and *T* evaluated from simulations of Hamon PET will also be investigated to address the consistency and discrepancy caused by using different PET methods.

3. Results

3.1 Projected changes in runoff~~*R*~~

Changes in mean annual *R* under future climate change scenarios vary among HUC-8 watersheds (Fig. 5) and WRRs (Fig. 6) across the CONUS. Runoff depletion is projected to cover most part of the ~~Midwest and South Central U.S.~~central CONUS across WRR7~WRR12, with largest decreases over 50% found in the south of WRR10 (Missouri) under RCP8.5. Increases are mainly projected in the Southwest, the north of ~~WRR10~~Missouri, and regions along the Atlantic Coast and Pacific Coast. Extreme increases over 100% are projected in several arid watersheds in WRR15 (Lower Colorado) and WRR16 (Great Basin). However, this may be caused by the inability of GCMs in reproducing the low *P* values in these extremely dry areas. Although the general spatial patterns appear to be similar in the four scenarios, there is an evident expansion of the areas showing either extreme increasing or decreasing trend from 2030s to 2080s under both RCP4.5 (Fig. 5a-5b) and RCP8.5 (Fig. 5c-5d) scenarios.

The large variability of regional changes in *R* (Fig. 6) indicates considerable uncertainties from GCM structure. In most cases, the uncertainty range is limited to −30% ~ +30%, showing both positive and negative changing signals. The distributions of the median lines and Inter-Quartile Ranges (IQRs) suggest a hydrologically drier future in WRR7~12 and WRR14 (Upper Colorado), where consistent decreasing signal is found in all the scenarios. ~~Stronger i~~Increasing trend can be found in WRR1 (New England), WRR2 (Mid-Atlantic), WRR17 (Pacific Northwest), and WRR18 (California). Generally, the uncertainty ranges tend to increase from 2030s to 2080s under both RCPs, and reach a particularly high level under RCP8.5/2080s. There is a noticeable consistency in ~~this~~ the pattern that the GCMs agree more on the simulations in 2030s while the uncertainty aggregates over time toward 2080s, which implies the limitation of the state-of-the-art GCMs in predicting farther future.

3.2 Independent effects of climate variables

The changes in *R* discussed above are under the combined impact of changing *P*, *T*, *Rs*, *Ws*, and *Sh*. The independent effects of these factors over the entire CONUS are illustrated in Fig.7a-7b. *P* and *T* are clearly the two most influential factors, which are projected to cause divergent changes in *R* due to the increase in *P* (+15 ~ +31 mm yr^{-1}) and *T* (+1.8 ~ +5.3 ℃). The median values show that annual *R* under the independent *P* effect is expected to increase by 13 mm yr^{-1} (4%) in 2030s and 24 mm yr^{-1} (8%) in 2080s under RCP4.5, and by 21 (7%) and 30 (10%) mm yr^{-1} at the same time under RCP8.5. In contrast, the independent effects of *T* reach -32 (-11%), -50 (-17%), -34 (-12%), and -80 (-28%) mm yr^{-1} in the scenarios S1~S4. The negative effect of rising *T* is expected to exceed the positive effect of increasing *P* and lead to overall decrease in *R*. However, *Sh*, the third largest contributor, will enhance *R* by 3%~12% and largely offset the *T* effects. Significant increasing trend in *Sh* is projected under both RCP4.5 and RCP8.5 (Fig. 3e), which will suppress vapor pressure deficit and thus partially counterbalance the increasing evaporative demand caused by warming. Meanwhile, the effects of *Rs* (slightly negative), *Ws* (slightly positive), and interactions among the factors (*Int*) are relatively minimal (<3%), suggesting that the variations in *T*, *P*, and *Sh* can explain the major changes in *R*.

It is worth noticing that much larger uncertainty ranges can be found in the *P* effects. Compared to the highly consistent increases in *T* and *Sh*, the 20 GCMs constantly disagree on the changing direction of *P*. Under RCP8.5/2080s, the multi-model result of *P* effect ranges from -11% to 24%, and the IQR also reaches the highest level (13%). It indicates that uncertainty in *P* projection is still the largest contributor to the uncertainty in *R* simulations, especially in the far future.

We also compared these results with those evaluated based on Hamon PET (Fig. 7c), and found some similar features. The differences in independent effects of *P* and *T* between the two sets of results are mostly smaller than 5%, and both results show that *T* effect would be twice as large as *P* effect at CONUS scale. This suggest that the bias in PET model structure is not likely to turn over the relative importance of *P* and *T* effects as long as E_T model is properly calibrated. However, the projected decreases in *R* (i.e., the 'Total' effects) are obviously more severe when using Hamon PET because the positive effect of increasing humidity is not considered.

3.3 Relative contributions of precipitation and temperature~~*P* and *T*~~

Table 2 summarizes the relative contributions of *P* and *T* to *R* change for the historical and future periods in 18 WRRs and the entire CONUS. Historical changes in *P*, *T*, and their effects on *R* were tested using PRISM climate data spanning from January 1960 to December 2010. Given the significant spatial and temporal variability in *R* trend across the CONUS (Mauget, 2003;McCabe and Wolock, 2002, 2011;Gupta et al., 2015), a consistent breakpoint is statistically unavailable. We hereby took 1985 as the breakpoint year for all the watersheds and evaluated the multi-decadal mean changes from 1961-1985 (pre-change period) to 1986-2010 (post-change period). Although the selection of different breakpoints may cause certain deviations, the analysis can provide a comparable benchmark for exploring the shifts in future scenarios at a multi-decadal scale. Unsurprisingly, the results of these latest decades show the prevailing role of *P* in nearly all the regions, with WRR14 being the only exception. In the future periods (from baseline to S1~S4), however, results derived from both PM and Hamon PET suggest that the role of *T* rise will surpass *P* and become the largest driver in most of the regions (15~16 out of 18 WRRs) in the future. In contrast, a larger mean contribution of *P* can be occasionally found in the Atlantic Coast (WRR1,2), Pacific Coast (WRR18), ~~coastal regions (WRR1, 2, 18)~~ and the Southwest (WRR12,~~–~~15). Considering that the inconsistency among ~~the different~~ GCMs may make the recognition of larger contributor dubious, we used Wilcoxon signed-rank test (Gibbons and Chakraborti, 2011) to assess the statistical significance of the difference between each pair of *P* and *T* contributions (i.e., 20 samples from the 20 GCMs). The test results reveal high agreement among GCMs on the prominent role of *T* across ~~a major~~most regions ~~part of the CONUS, particularly the Midwest (WRR4~11) and the Mountain West (WRR14,16)~~ (underlined in Table 2).

At CONUS level, the mean contributions of *P* and *T* are projected to lie within

20%~24% and 43%~50% using PM PET, and 33%~40% and 55%~62% using Hamon PET, suggesting a similar shift in the relative importance of these two key driving factors. However, future changes in *Sh*, *Rs*, and *Ws* account for another 16%~23%, 2%~7%, and 1%~4% of *R* change respectively, and indirectly affect the attributions to *P* and *T*. For example, the *R* increase in WRR1 would be completely attributed to *P* increase if *Sh* was not considered, and thus lead to an overestimation of *P* contribution. ~~Also, we caution that spatially various levels of uncertainty are involved due to the diverse changing directions and magnitudes of climatic variables projected by different models.~~

3.4 Spatial distribution of the major driving factors

To further investigate the spatial pattern of future climatic controls on annual *R*, we mapped the coverage of dominant driving factors (Fig. 8) and examined its consistency with the changing trend in *R* at watershed scale (~~Fig. 8 &~~ Table 3). Judging by multi-model ensemble means, *P* and *T* are the largest driving factor in 10%~22% and 68%~89% of the CONUS area. High consistency on their dominant roles (80% or more of the 20 GCMs agree on the sign) can be found in 4%~7% and 21%~41% of the CONUS, respectivley. As *P* and *T* are projected to keep increasing, the coverages of *P*-dominant and *T*-dominant areas are also expected to expand from 2030s to 2080s. A directional change suggests that rising *T* will become more influential in the east (WRR1~6), while *P* will prevail in more watersheds across the west (WRR13~18). Although the aggregated effect of *Sh* is quite close to that of *P* at large scales, it is only expected to play a dominant role in several watersheds (1% in area) across the borders between

WRR10 and WRR11 under RCP8.5/2080s.

The *P*-dominant areas that mainly distributed in the Southwest (WRR13,15) and Pacific Coast (WRR17,18) show clear signals of increasing *R*, driven by the widespread increase in *P*. One the other hand, only two thirds ~~61%~68%~~ of the *T*-dominant areas coincide with the areas of decreasing R, covering a large part of the ~~Midwest~~ central CONUS (WRR7,~~-~~9~~∼~~,10,11) and a number of watersheds scattered in the ~~Mountain West~~Northwest (WRR14,~~-~~16,~~-~~17). Although *T* is also identified as the most influential factor in the ~~East~~ eastern regions ~~(~~WRR1∼5~~) by 2080s~~, the combined effect of other four factors, primarily *P* and *Sh*, is projected to exceed the *T* effect and lead to an increase in *R*.

4. Discussion

4.1 Spatial patterns of future runoff change~~s in *R*~~

This study characterizes and generalizes large-scale relationships among changing *P*, *T*, and *R* despite the large geographic differences. The coherence in the spatial dynamics of *R* trend and the corresponding climatic drivers shows a rough pattern: *T* change dominates *R* decrease while *P* and *Sh* changes dominate *R* increase. However, it should be interpreted with limitations on time scale and underlying surface features. This pattern does not hold true in all the watersheds due to the nonlinear complexity of *R* response to climate change at various time scales, as well as the influence of other watershed characteristics (e.g., topography, land-use, soil property). For example, slight decreases in annual *P* but somewhat increases in annual *R* are projected in south Texas due to the ~~alteration of~~changes in ~~inner~~intra-annual climate variability. The role of *T* may also become more positive in regions where water availability is dominated by snow melting (Barnett et al., 2005;Lutz et al., 2014). Besides, local R can be affected by other factors, such as land-cover evolution and the direct effects of atmospheric composition on transpiration (Gedney et al., 2006;Zhang et al., 2001;Zhang et al., 2015).

4.2 The role of land cover and land use

Land cover, LAI, and soil are important controls on catchment water balance and R sensitivity to climate change (Zhang et al., 2001;Bosch and Hewlett, 1982;Cheng et al., 2014). This study specifically focused on evaluating the separate and combined effects of changing climates on R within a static land cover/land use. We did not consider the potential evolution of land cover and its interactions with water balance. We made no explicit tabulation of the impact of land cover/land use on the R responses to climate change, but we did incorporate it as a key factor by estimating E_T with a set of functions of climate, LAI, and soil moisture capacity and deficit. Across the land cover classes, the uncertainty ranges of independent contributions of P (13%~30%) and T (39%~51%) are relatively small compared to the ranges across WRRs (18%~47% and 29%~52%). This may be because the discrepancy across different land covers is largely offset by the different climate backgrounds across the country. Evaluation of future land cover change and its impact on R is out of the scope of this study. However, our results imply that the potential impact of land cover change might not be large enough to alter the relative significance of P and T in controlling future continental water availability.

4.3 Implications for water and land management

Our results have important implications for water and land management across the

CONUS. Water resources planning may need to prepare different management strategies for areas facing contrasting future hydrological conditions. Additional water storage such as reservoirs ~~and flood prevention measures~~ may be needed in regions expecting more *R*, while inter-basin water transfer, improving water use efficiency, and other water conservation measures such as rain harvesting, and waste water recycling should be implemented for areas expecting water shortages. The vast croplands across central U.S. are likely to be threatened by rising *T* and diminishing water availability for irrigation and food production. Adaptations in cropping systems and irrigation strategy are needed to secure food supply and increase resiliency to drought and changing climate (Challinor et al., 2014;Teixeira et al., 2013). The drier and hotter conditions may also result in increasing water stress, higher risks of tree insects and disease outbreaks, and catastrophic wildfires in forests (Dale et al., 2001) (e.g., National Forests in WRR14, 16, 17) and grasslands (e.g., in WRR10~11). Innovative land management practices such as forest thinning and fuel management, irrigation, and planting drought-tolerant species are vital to minimize the potential risk and vulnerability to climate change and reduce the threats to ecosystems and society (Sun et al., 2015a;Grant et al., 2013;Vose et al., 2016).

4.4 Uncertainties and caveats

Considerable uncertainty lies in the projection of future climate changes from the 20 GCMs. The uncertainty ranges under both RCP4.5 and RCP8.5 show significant expansions over time from 2030s to 2080s. In particular, the large uncertainty in predicting future *P* may substantially compromise the reliability in evaluating either *R* change or the roles of P and T (Karl and Riebsame, 1989;Piao et al., 2010). Although the results allow us to draw some conclusions on the general patterns, uncertainties are large and vary differently across space and time. There are certain limitations in this evaluation that should be noted when interpreting the results. First, we did not incorporate other sources of uncertainty, such as the methodology of downscaling (Duan and Mei, 2014a;Chen et al., 2011), and structure and parameters of hydrologic model (Jung et al., 2012). Although the selections of GCM and emission scenario are more likely to be the largest sources of uncertainty in hydro-climatic modeling (Kay et al., 2009;Wilby and Harris, 2006;Duan and Mei, 2014b), the other sources may also affect the results to different extents. The roles of uncertainties from different sources can be particularly equivocal when investigating seasonal/monthly variability and extreme events (Bosshard et al., 2013;Giuntoli et al., 2015;Bae et al., 2011;Kay et al., 2009). Second, we focused on the independent effects of potential climate changes ~~in this study~~, while assuming the inter-relationship among the meteorological variables and water-balance components remains the same as in historical periods. In future studies, improved climate datasets and better representation of the physical mechanisms of climatic factors (e.g., radiation, Bohn et al., 2013; wind speed, McVicar et al., 2012) are needed to reduce uncertainties.

5. Conclusions

This study evaluates the relative roles of precipitation and air temperature, as well as solar radiation, wind speed, and air humidity, in altering annual runoff across the CONUS based on a large ensemble of simulations using data from both historical measurements and CMIP5 GCMs projections. Despite the large uncertainty and spatial variability involved in the results, two robust conclusions can be drawn at the CONUS and regional scales on multi-decadal basis. First, the role of temperature will outweigh that of precipitation in a continued warming future in the 21st century, in spite that precipitation has been the primary control of runoff variation during the latest decades. The projections from 20 climate models suggest a high degree of consistency on the increasing trends in both precipitation and temperature, but the negative effect of temperature is expected to exceed the positive effect of precipitation on runoff change in most regions. Over the entire CONUS, temperature is projected to be the largest contributor (43%~50%), followed by precipitation (20%~24%), humidity (16%~23%), solar radiation (2%~7%), and wind speed (1%~4%). Spatially, precipitation is likely to be the dominant driving factor for runoff increase across the Pacific Coast and the Southwest, while temperature will be more influential in the central CONUS and parts of the ~~Mountain West~~Northwest and cause runoff decreases. ~~Particularly, the vast areas of croplands and grasslands across the Midwest and forests in the Mountain West might be under severe threat of water supply decline caused by warming.~~

Second, increasing humidity is expected to partially offset the additional evaporative demand caused by warming, and consequently enhance runoff wide across the country. Although the rising temperature is projected to be the largest control of runoff change in the eastern CONUS, the combined effects of increasing humidity and precipitation will surpass the detrimental effects of warming and result in a hydrologically wetter future. This study also raises concern on the choice of PET method. It has been well acknowledged in ~~meteor-hydrology~~hydrometeorological communities that temperature-based PET methods tend~~s~~ to be oversensitive to temperature change. Our results further demonstrate that the main risk of using temperature-based PET is overlooking the effects of other changing climatic variables (mainly humidity in this case), which have not been as widely measured as temperature and are relatively understudied, rather than overestimating the effects of temperature.

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Competing interests. The authors declare that they have no conflict of interest.

Tables

Table 1. List of the 20 climate models and the changes in mean annual precipitation and temperature over the conterminous United States (CONUS) from the baseline scenario (B) to future scenarios S1 (RCP4.5/2030s), S2 (RCP4.5/2080s), S3 (RCP8.5/2030s), and S4 (RCP8.5/2080s).

GCM	Country	Precipitation (mm yr^{-1})					Temperature (°C)				
		B	S1	S2	S3	S4	B	S1	S2	S3	S4
bcc-csm1-1	China	787	-3	+13	+33	-5	11.4	+1.7	+2.4	+1.9	+4.8
bcc-csm1-1-m	China	786	+18	-18	+29	+33	11.4	+1.5	+2.4	+1.7	+4.3
BNU-ESM	China	798	+51	+42	+25	+45	11.5	+1.9	+3.2	+2.0	+5.4
CanESM2	Canada	800	+14	+42	+19	+83	11.3	+2.3	+3.5	+2.4	+5.8
CCSM4	USA	783	+29	+29	+18	+58	11.5	+1.5	+2.5	+1.9	+4.6
CNRM-CM5	France	780	+46	+56	+40	+85	11.4	+1.4	+2.8	+1.6	+4.6
CSIRO-Mk3-6-0	Australia	780	+14	+84	+24	+74	11.2	+2.0	+3.4	+2.0	+5.6
GFDL-ESM2M	USA	787	+6	+20	+32	+31	11.3	+1.6	+2.2	+1.7	+4.2
GFDL-ESM2G	USA	791	+21	+36	+38	+12	11.4	+1.2	+1.7	+1.2	+3.7
HadGEM2-ES	UK	784	+16	+7	+18	+7	11.3	+2.2	+3.8	+2.5	+6.8
HadGEM2-CC	UK	779	+23	+39	+5	+32	11.3	+2.3	+4.2	+2.7	+6.7
inmcm4	Russia	779	-7	+4	+0	+13	11.4	+0.9	+1.7	+1.1	+3.4
IPSL-CM5A-LR	France	780	+8	+14	+13	-8	11.5	+1.8	+3.0	+1.8	+5.8
IPSL-CM5A-MR	France	789	-4	+13	-25	-70	11.3	+1.9	+3.2	+2.3	+6.0
IPSL-CM5B-LR	France	781	+23	+62	+34	+82	11.4	+1.5	+2.4	+1.7	+4.4
MIROC5	Japan	788	+9	+10	+24	+6	11.2	+2.3	+3.6	+2.4	+5.7
MIROC-ESM	Japan	791	+56	+37	+30	+9	11.3	+2.1	+4.1	+2.6	+6.6
MIROC-ESM-CHEM	Japan	784	+12	+38	+26	+10	11.4	+2.4	+4.0	+2.7	+6.9
MRI-CGCM3	Japan	783	+20	+47	+38	+87	11.4	+0.8	+1.7	+1.0	+3.2
NorESM1-M	Norway	784	+13	+31	+25	+63	11.3	+1.8	+3.1	+2.2	+5.1

Table 2. Comparison of multi-model averaged contributions (%) of precipitation (*P*) and temperature (*T*) to changes in runoff in the 18 Water Resource Regions (WRRs) and entire CONUS in historical period (1961-2010) and future scenarios S1 (RCP4.5/2030s), S2 (RCP4.5/2080s), S3 (RCP8.5/2030s), and S4 (RCP8.5/2080s). The larger contributor identified by multi-model ensemble means is bolded, and the significant larger contributor identified by Wilcoxon signed-rank test (at 5% significance) is underlined.

WRR	Historical		Projections based on PM PET								Projections based on Hamon PET							
			S1		S2		S3		S4		S1		S2		S3		S4	
	P	*T*	*P*	*T*	*P*	*T*	*P*	*T*	*P*	*T*	*P*	*T*	*P*	*T*	*P*	*T*	*P*	*T*
1	**88**	9	36	**36**	36	**38**	34	**38**	31	**42**	**61**	38	**58**	40	**57**	41	**53**	46
2	**80**	17	27	**40**	28	**41**	30	**39**	28	**43**	47	**50**	49	**50**	**51**	47	46	**52**
3	**60**	30	31	**37**	26	**41**	30	**38**	24	**44**	43	**49**	38	**56**	41	**52**	32	**60**
4	**83**	13	24	**44**	23	**46**	29	**41**	23	**47**	44	**54**	42	**57**	**50**	48	40	**58**
5	**73**	22	23	**42**	23	**44**	29	**40**	25	**46**	40	**57**	38	**59**	46	**51**	37	**60**
6	**64**	30	28	**40**	27	**42**	32	**38**	26	**45**	41	**54**	40	**56**	46	**49**	37	**58**
7	**89**	6	23	**47**	19	**51**	23	**48**	20	**52**	40	**57**	32	**65**	37	**59**	32	**65**
8	**48**	37	27	**39**	23	**43**	24	**42**	24	**46**	38	**53**	34	**58**	35	**56**	29	**61**
9	**89**	8	22	**47**	20	**49**	26	**45**	20	**43**	37	**56**	34	**61**	40	**53**	33	**57**
10	**81**	6	19	**47**	18	**50**	18	**49**	20	**46**	35	**57**	32	**62**	32	**60**	33	**59**
11	**88**	4	20	**42**	19	**45**	18	**44**	18	**47**	30	**55**	29	**60**	27	**58**	26	**63**
12	**74**	14	**35**	29	27	**35**	30	**32**	27	**39**	**44**	38	37	**46**	38	**42**	31	**51**
13	**71**	18	25	**36**	27	**38**	26	**35**	22	**42**	35	**53**	36	**56**	37	**53**	28	**61**
14	30	**51**	21	**48**	25	**48**	20	**49**	24	**49**	31	**64**	36	**60**	32	**64**	31	**61**
15	**72**	17	28	**33**	**36**	32	**33**	32	**36**	29	35	**52**	41	**48**	43	**47**	37	**49**
16	**65**	23	21	**45**	24	**46**	23	**45**	29	**43**	34	**59**	36	**58**	32	**60**	38	**51**
17	**91**	7	28	**42**	28	**43**	29	**42**	31	**42**	44	**54**	44	**54**	45	**53**	47	**51**
18	**95**	4	**47**	29	**43**	32	**46**	30	**46**	30	**58**	36	**54**	41	**56**	39	**54**	42

CONUS	**57**	29	20	**45**	20	**47**	24	**43**	21	**50**	35	**58**	35	**60**	40	**55**	33	**62**

Table 3. Cross comparison of the areal proportions (%) with different dominant driving factors and changing directions of runoff (*R*) in the future scenarios S1 (RCP4.5/2030s), S2 (RCP4.5/2080s), S3 (RCP8.5/2030s), and S4 (RCP8.5/2080s). ~~The climate variable is identified as 'dominant' when 80% or more of the 20 GCMs agree that it is the largest driving factor of runoff change.~~ The areas where a variable is the largest driving factor identified by multi-model ensemble means is marked in the brackets~~,~~. ~~and t~~The areas where a variable is identified as the 'dominant' ~~with a significant dominant~~ factor ~~is~~ are bolded. A climate variable is identified as the 'dominant' one only when 80% or more of the 20 GCMs agree that it is the largest driving factor of runoff change.

Scenario	S1	S2	S3	S4
Precipitation				
R↗[a]	**4** (10)	**7** (17)	**6** (15)	**6** (21)
R↘	**0.2** (0.2)	0	**0.2** (0.2)	0 (0.7)
Temperature				
R↗	**9** (51)	**15** (45)	**7** (55)	**13** (26)
R↘	**15** (38)	**23** (37)	**14** (30)	**28** (42)
~~*Solar radiation*~~				
~~*R*↗~~	~~0~~	~~0~~	~~0~~	~~0~~
~~*R*↘~~	~~0~~	~~0~~	~~0~~	~~0~~
~~*Wind speed*~~				
~~*R*↗~~	~~0~~	~~0~~	~~0~~	~~0~~
~~*R*↘~~	~~0~~	~~0~~	~~0~~	~~0~~
Specific humidity				
R↗	0 (0.2)	0 (2)	0 (0.2)	**0.8** (5)
R↘	0 (0.2)	0 (0.4)	0	**1** (5)

[a] "↗" and "↘" indicate increase and decrease in the multi-model means of runoff, respectively.

Figures

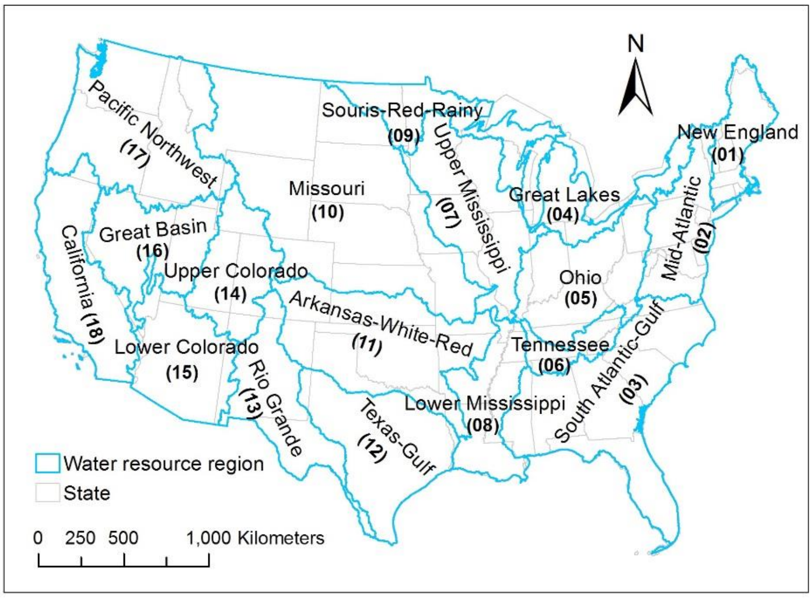
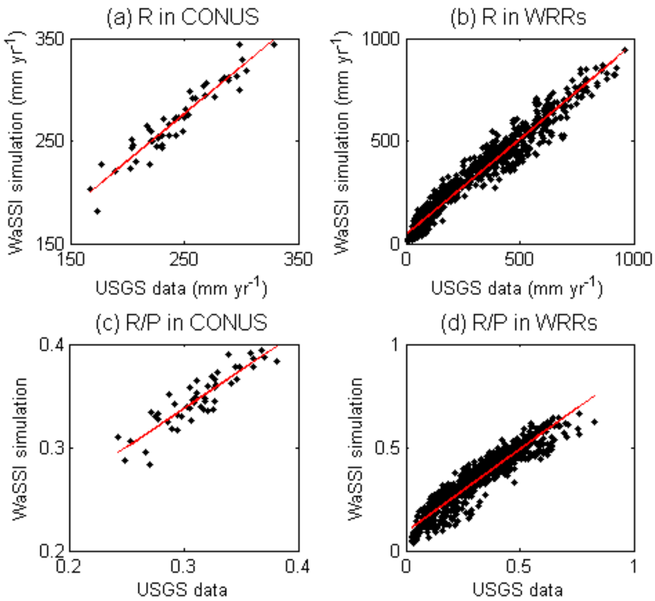


Figure 1. ~~(**a**) Land cover distribution in the conterminous United States (CONUS) from the 2006 National Land Cover Database (http://www.mrlc.gov/nlcd06_data.php), and (**b**) l~~Location of the 18 Water Resource Regions (WRRs)~~.~~ in the conterminous United States (CONUS).



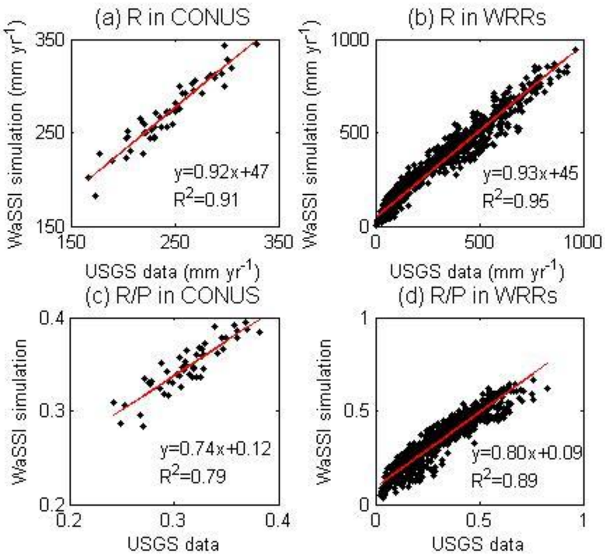


Figure 2. Validations of the WaSSI model at the conterminous United States (CONUS) and Water Resource Region (WRR) levels. **a-b**, Comparisons of simulated annual runoff (*R*) (mm yr^{-1}) against USGS observed data in 1961-2010 over the entire CONUS (**a**) and in 18 WRRs (**b**). **c-d**, Comparisons of simulated runoff coefficient (runoff/precipitation, R/P) against that derived from USGS observed data in the CONUS (**c**) and WRRs (**d**).

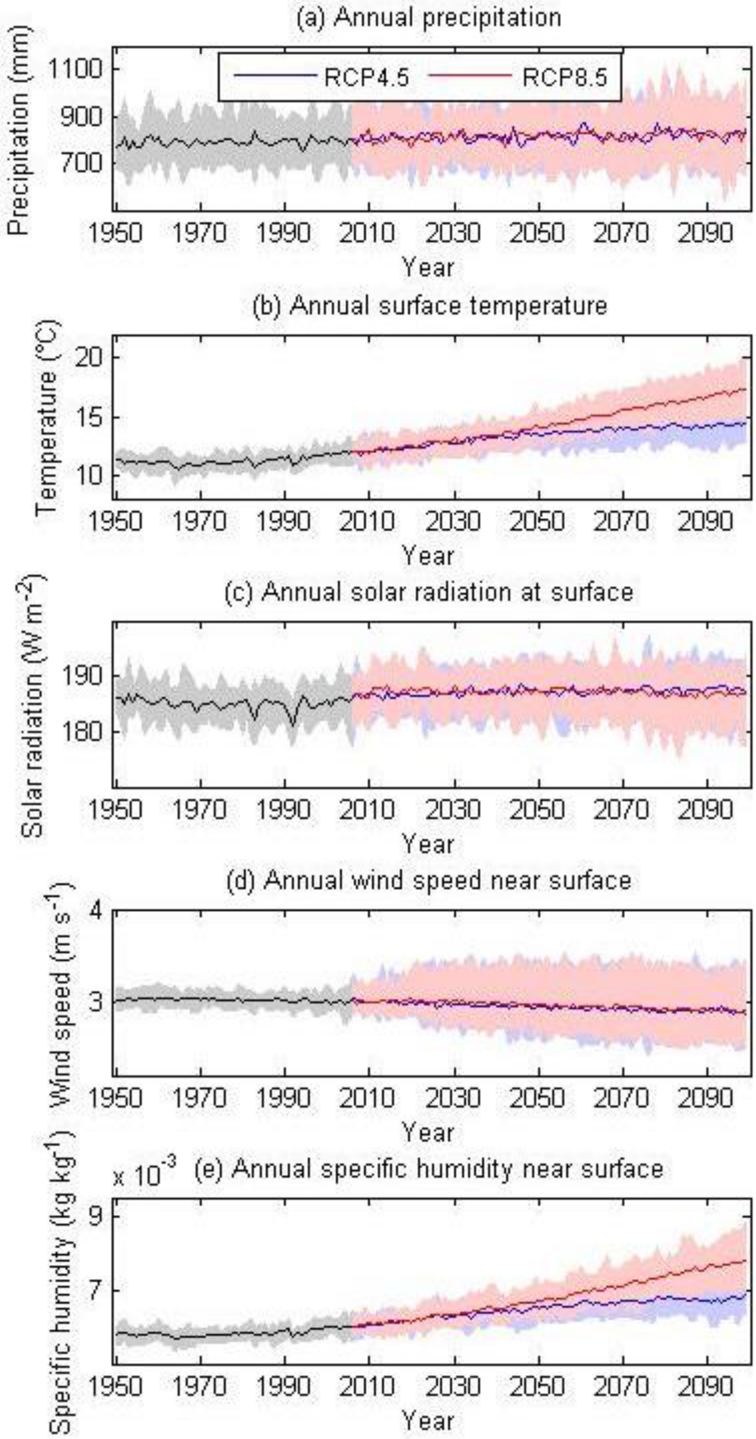


Figure 3. Temporal variations of annual mean precipitation (**a**), surface air temperature (**b**), solar radiation at surface (**c**), wind speed near surface (**d**), and specific humidity near surface (**e**) over the CONUS. Thick lines and the shading denote the multi-model ensemble means and uncertainty ranges of the 20 GCMs, respectively.

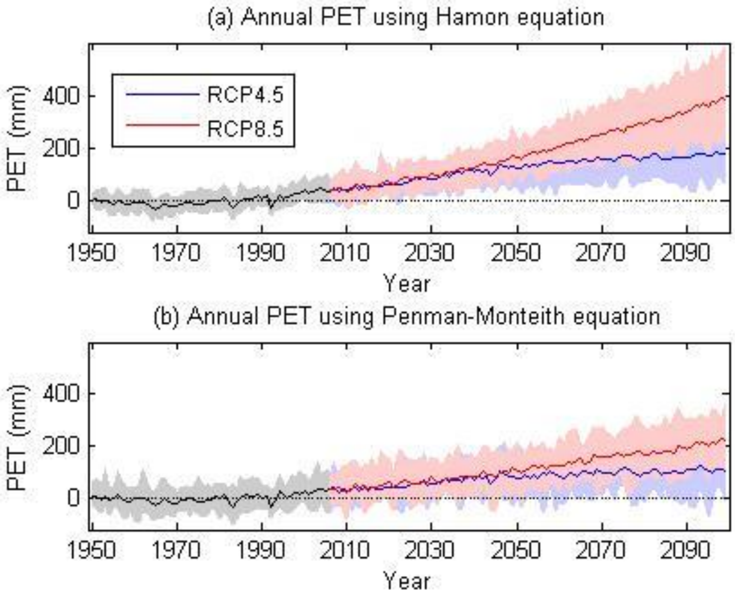


Figure 4. Temporal variations of changes in annual potential evapotranspiration (PET) over the CONUS against the baseline level (1970-1999). Thick lines and the shading denote the ensemble means and uncertainty ranges of the 20 GCMs, respectively.

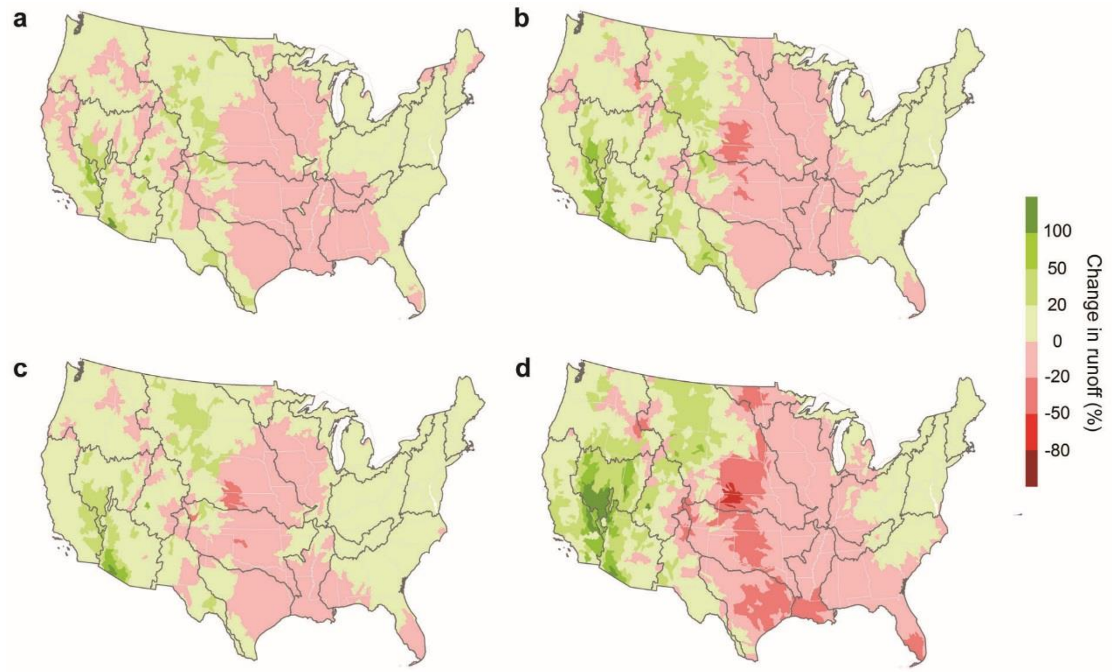


Figure 5. Projected changes in multi-year mean annual runoff (%) at HUC-8 watershed scale. **a-d**, Changes from the baseline to S1 (RCP4.5/2030s) (**a**), S2 (RCP4.5/2080s) (**b**), S3 (RCP8.5/2030s) (**c**), and S4 (RCP8.5/2080s) (**d**) scenarios. The maps display the multi-model mean changes from the 20 GCMs.

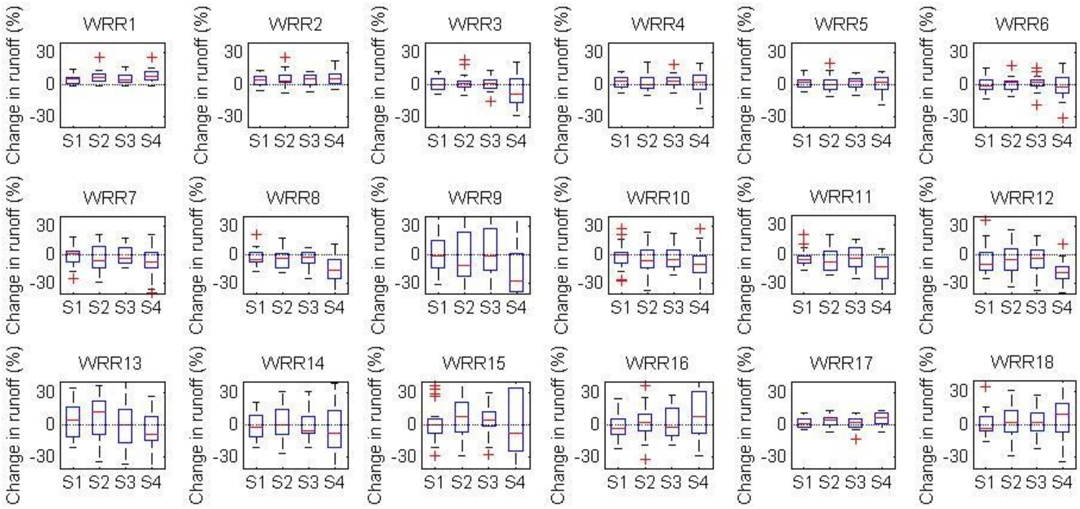


Figure 6. Area-averaged changes in runoff in the 18 Water Resource Regions (WRRs) in the future scenarios. The four future scenarios are denoted by S1 (RCP4.5/2030s), S2 (RCP4.5/2080s), S3 (RCP8.5/2030s), and S4 (RCP8.5/2080s) in the x-axis. The vertical spread of the box-whisker plots shows the different results projected from the 20 GCMs, with the boxes covering the ranges from 25% quartile to 75% quartile of the distributions (Inter-Quartile Range, IQR) and the red lines within each box marking the median values. Points outside the whiskers are taken as extreme outliers and marked by plus signs.

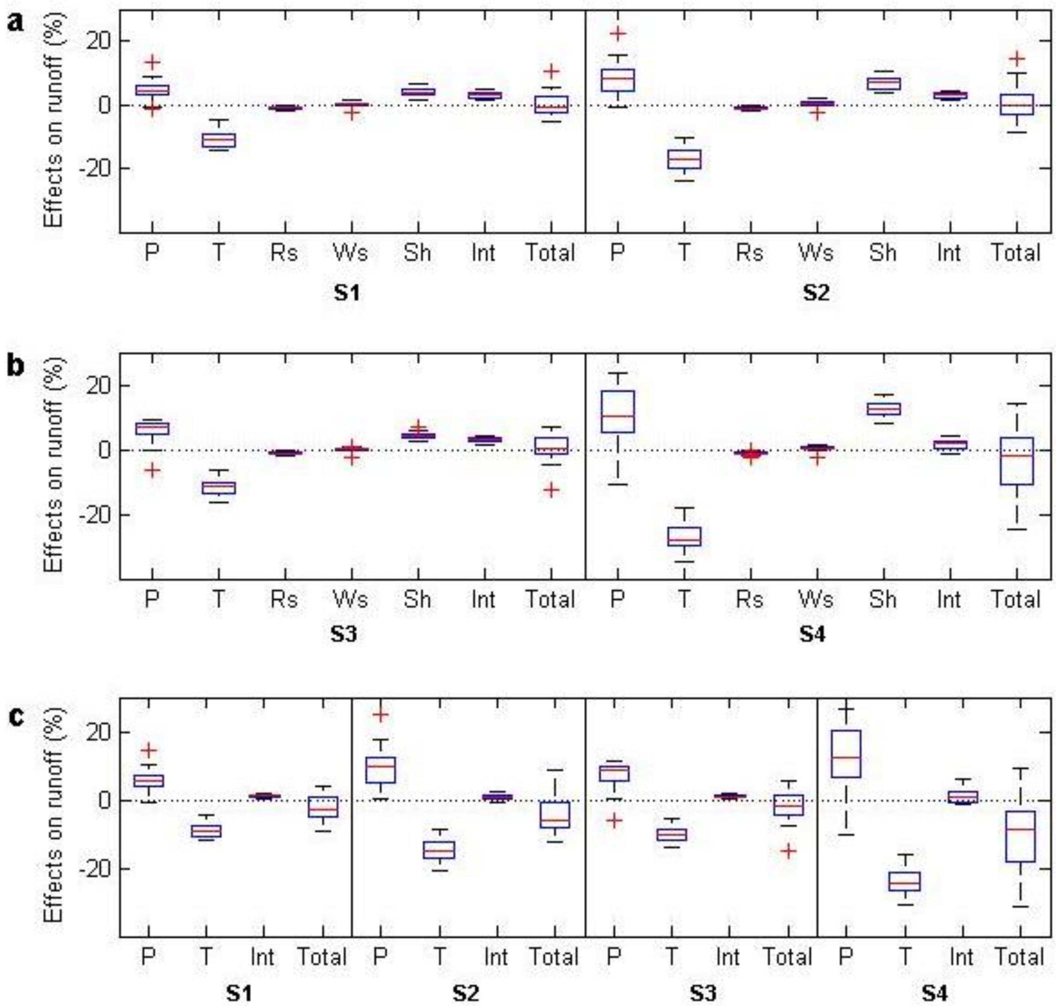


Figure 7. Independent effects of the climate variables over the conterminous United States (CONUS) in the future scenarios S1 (RCP4.5/2030s), S2 (RCP4.5/2080s), S3 (RCP8.5/2030s), and S4 (RCP8.5/2080s). **a-b**, Effects of precipitation (*P*), temperature (*T*), solar radiation (*Rs*), wind speed (*Ws*), specific humidity (*Sh*), interactions among the variables (*Int*), and their sum (*Total*) on runoff based on the projections of Penman-Monteith PET. **c**, Effects of precipitation (*P*), temperature (*T*), interaction between *P* and *T* (*Int*), and their sum (Total) on runoff based on the projections of Hamon PET. The format of the box-whisker plots is the same as that in Figure 6.

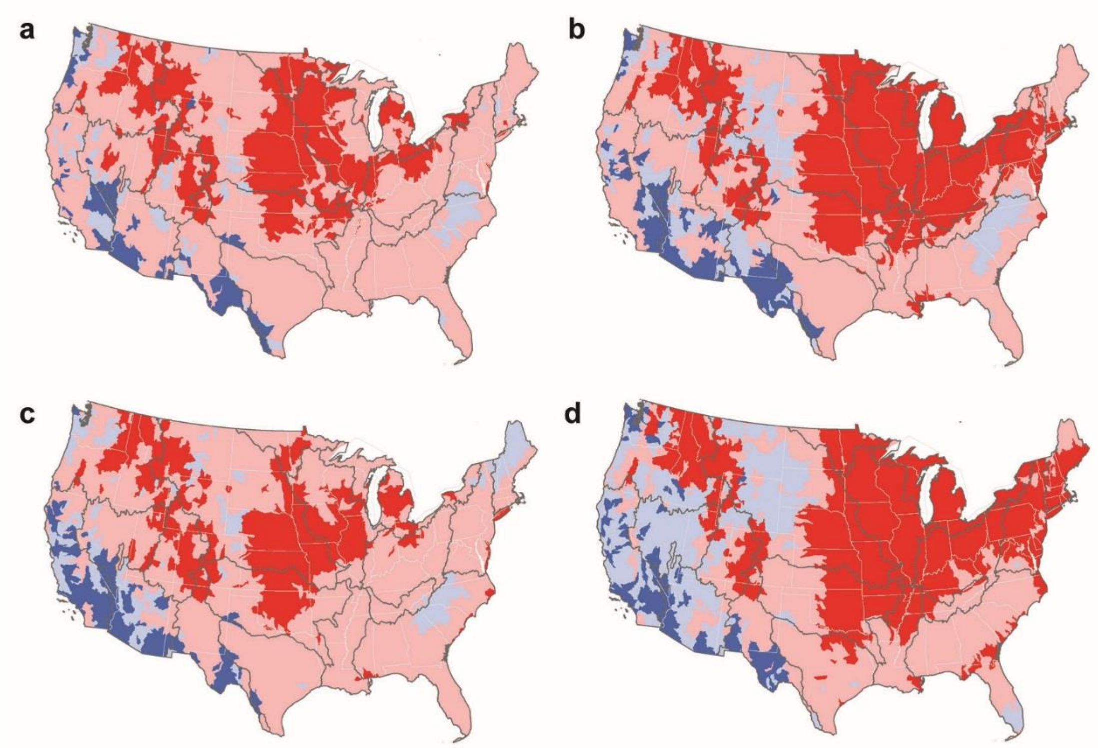


Figure 8. Relative importance of P and T in affecting runoff change across the HUC-8 watersheds in the future scenarios of S1 (RCP4.5/2030s) (**a**), S2 (RCP4.5/2080s) (**b**), S3 (RCP8.5/2030s) (**c**), and S4 (RCP8.5/2080s) (**d**). The watersheds under larger influence of P and T are marked with blue and red colors, respectively. The dark colors denote the areas where 80% or more of the 20 GCMs agree on the sign, while the light colors denote the results of ensemble average.