Dear Editor and Reviewers:

On behalf of all the contributing authors, I would like to express our sincere appreciations of your letter and reviewers' constructive comments concerning our article entitled "Responses of runoff to historical and future climate variability over China" (Manuscript No.: **hess-2017-98**). Those comments are all valuable and very helpful for revising and improving our paper, as well as the important guiding significance to our researches. We have studied comments carefully and have made correction which we hope meet with approval. In this revised version, changes to our manuscript were all highlighted within the document by using red colored text. Point-by-point responses to the nice editor and two nice reviewers are listed below this letter.

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Editor comments:

I think the authors have responded to some critical comments well. I do class this paper as requiring major corrections to answer some of these points and that is in agreement with both reviewers. Please can the authors submit a revised manuscript that will be further reviewed by both the current reviewers. To add to the authors comments I note the following that I would like to see more developed:

Reviewer 1, comment 1: I think there needs to be a more quantified answer to whether or not the modelled results may impact the elasticities calculated. I'm not sure I agree that a calibration scheme that is focused on high flows and having some uncertainty (as all models do) means that 'annual' outputs are more accurate. I can imagine the extent of that is catchment response dependent... So ensure this effect is proved by the manuscripts analyses. Please note that the reviews are asking for a treatment of the uncertainties in the modelling and this is not all about different PET calculations in my view....

Also I will want to make sure then authors identify and are seen to be dealing with the issues of hydrological model simulations to future climates and how 'valid' there modelling system is for achieving this (from the GCM's downwards through the hydrological cascade).

Response: Thank you very much for your nice comments. We quite agree with you that there needs to be a more quantified answer to whether or not the modelled results may impact the elasticities calculated. According to your good suggestion, we further made a sensitivity analysis on the changes in *P* elasticity and *PET* elasticity in response to changes in runoff (*R*) for the 14 river basins in China (As shown in Figure 14 in the revised MS). We found that the sensitivity of climate (i.e., *P* and *PET*) elasticity to *R* varies considerably between basins and tends to be larger in more humid basins. Moreover, *PET* elasticity is more sensitive to changes in *R* compared with *P* elasticity for all 14 basins. As indicated by Zhang et al. (2014), the *R* is realistically estimated for most of the basins (especially for humid basins) in China with a small relative error, but there is a large relative error for few arid basins in western China due to the lack of meteorological observations. Therefore, these errors in simulated *R* of the VIC model may result in uncertainties in elasticity calculation, particularly in western China. For more information please see lines 396-403 in the revised MS.

To address the issues of hydrological simulations to future climate change, our study firstly calculated the climate (i.e., *P* and *PET*) elasticity of *R* (i.e., per change in *R* due to per change in *P* and *PET*) over China by the Budyko-based elasticity method, based on the land surface data from the VIC model (Zhang et al., 2014). Then we projected changes in climate (i.e., changes in *P* and *PET*) over the 0.5 degree grids of China during the period 2071-2100 in RCPs 4.5 and 8.5 compared with the baseline period (1971-2000), by using the downscaling results of the 28 GCMs. By neglecting the catchment properties elasticity, the projected changes in *P* and *PET* over China from the 28 GCMs were taken into equation (4) (as shown in the revised MS) to project future hydrological changes (i.e. projected changes in *R*) due to climate change during the period 2071-2100 in RCPs 4.5 and 8.5. We think climate elasticity concept is neat for the issues of hydrological responses to an ensemble of climate change projections.

Reference:

Zhang, X., Tang, Q., Pan, M., Tang, Y.: A Long-Term Land Surface Hydrologic Fluxes and States Dataset for China, J. Hydrometeor., 15, 2067–2084, doi: 10.1175/JHM-D-13-0170.1, 2014.

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Anonymous Referee #1:

This paper describes the projected effects of climate change on runoff and water availability in China using a framework based on runoff elasticity. In general the paper is well written and of sufficiently wide geographical scope to be interesting to a broad readership, but several key assumptions in the methodology, which are neither documented nor discussed, preclude a recommendation to publish without major revisions. These are:

1. More information on the parameters used in the hydrological modeling is necessary, especially those used with VIC to calculate runoff. These assumptions lie at the heart of the elasticities calculated, which will be heavily influenced by the structure and parametrisation of that model. [Section 2.1 Line 5]

Response: Thank you very much for your nice comments. In our study, the Budyko framework with an empirical parameter was used to calculate climate elasticity of runoff (*R*), and this method has been proven to be robust to the calculation of climate elasticity (Yang et al., 2014). For the VIC model used for the calculation of runoff, the parameters include: the infiltration parameter *b*, the second and third soil layer depths (d_2 and d_3), and the three parameters in the base flow scheme. According to Zhang et al (2014), the VIC model was calibrated in the 11 major basins over China based on the best meteorological forcing data (derived by 756 meteorological stations over China). The model parameters were estimated by using an optimization algorithm of the multi-objective complex evolution of the University of Arizona (MOCOM-UA). According to your good comments, we have added more information on the parameters in the VIC modeling in the revised MS. For detailed information please see lines 89-93 in the revised MS.

In addition, we made a sensitivity analysis on the changes in *P* elasticity and *PET* elasticity in response to changes in *R* for the 14 river basins in China (As shown in Figure 14 in the revised MS). We found that the sensitivity of climate (i.e., *P* and *PET*) elasticity to *R* varies considerably between basins and tends to be larger in more humid basins. Moreover, *PET* elasticity is more sensitive to changes in *R* compared with *P* elasticity. As indicated by Zhang et al. (2014), the *R* is realistically estimated for most of the basins (especially for humid basins) in China with a small relative error, but there is a large relative error for few arid basins in western China due to the lack of meteorological observations. Therefore, the results suggest that the errors in simulated *R* of the VIC model may result in uncertainties in elasticity calculation, particularly in western China. For more information please see lines 396-403 in the revised MS.

Reference:

Yang, H., Qi, J., Xu, X., Yang, D., and Lv, H.: The regional variation in climate elasticity and climate contribution to runoff across China. J. hydrol., 517, 607-616, 2014.
Zhang, X., Tang, Q., Pan, M., Tang, Y.: A Long-Term Land Surface Hydrologic Fluxes and States Dataset for China, J.

Hydrometeor., 15, 2067–2084, doi: 10.1175/JHM-D-13-0170.1, 2014.

2. There is some discussion of uncertainty in Section 4.3 but it is very general and not quantitative. In particular, the detailed choice of which formulation of the Budyko model used to compute elasticities is investigated but neither the runoff model nor the *PET* equation are examined in this regard.

Response: Thank you very much for your nice comments. We agree with you that the discussion section is lack of quantitative analysis, especially for the examination of the estimation of runoff or *PET*. In our original version (i.e. initial submission), the *PET* of the 28 GCMs for the baseline 1971–2000 and the future period 2071–2100 was estimated by the Thornthwaite method. We noted that the Thornthwaite method is solely based on monthly temperature, which may tend to underestimate *PET* in the arid areas and overestimate *PET* in the humid areas. Therefore, we used a multiplicative correction for *PET* bias correction of the 28 GCMs (as shown in equation (1) in the revised MS).

According to your good suggestions, we compared four different *PET* calculation equations (i.e., the Penman method, the Thornthwaite method, the FAO-56 Penman–Monteith method, and the Thornthwaite method corrected by equation (1) in the revised MS) over the 14 river basins of China, and conducted a quantitative analysis of the impacts of the *PET* calculations on the *PET* elasticity calculations (as shown in Figure 13 in the revised MS). The results showed that the mean annual *PET* by the Penman method, the FAO-56 Penman–Monteith method, and the Thornthwaite method corrected by equation (1) are quite consistent, and the *PET* elasticity calculations from these three methods give very similar results in all 14 basins. In summary, our study suggests that the estimation of *PET* elasticity is robust to the *PET* estimated from the Penman method, the FAO-56 method, and the Thornthwaite method corrected by equation (1), but is not robust to the Thornthwaite method. For more information please see section 4.2 in the revised MS.

We also made a discussion on the comparison of changes in *P* elasticity and *PET* elasticity in response to changes in *R* for the 14 river basins in China (As shown in Figure 14 in the revised MS). It was found that the sensitivity of climate (i.e., *P* and *PET*) elasticity to *R* varies considerably between basins and tends to be larger in more humid basins. Moreover, *PET* elasticity is more sensitive to changes in *R* compared with *P* elasticity. As shown in Zhang et al. (2014), the *R* is realistically estimated for most of the basins (especially for humid basins) in China with a small relative error. However, there is a large relative error for few arid basins in western China due to the lack of meteorological observations. Therefore, our results suggest that the errors in simulated *R* of the VIC model may result in uncertainties in elasticity calculation, and this is particularly in western China. For more information please see lines 396-403 in the revised MS.

Reference:

Zhang, X., Tang, Q., Pan, M., Tang, Y.: A Long-Term Land Surface Hydrologic Fluxes and States Dataset for China, J. Hydrometeor., 15, 2067–2084, doi: 10.1175/JHM-D-13-0170.1, 2014.

3. *PET* is calculated using the Thornthwaite method, which is a surprise since with the data available there is information to justify the use of more physically accurate *PET* calculations. Justification for the use of the temperature-based Thornthwaite method is required, especially given that it may oversimplify (and artificially constrain) the results of the Budyko calculation which features subsequently. [P5 line 5]

Response: Thank you very much for your nice comments. In the original version (i.e. initial submitted manuscript), the *PET* data used for the calculation of climate elasticity are derived from the CRU TS3.22 dataset as produced by the Climatic Research Unit (CRU) at the University of East Anglia (Harris et al., 2014). In this dataset, the *PET* is calculated from the FAO Penman-Monteith method. In contrast, the *PET* of 28 GCMs is estimated by the Thornthwaite method. We fully agree with you that the temperature-based Thornthwaite method is lack of physical basis, and it is necessary to justify the use of the temperature-based Thornthwaite method and the use of more physically *PET* calculation methods.

In the revised manuscript, we used a more physically *PET* data that estimated by the Penman method (during the period 1960–2008 provided by the Hydroclimatology Group of Princeton University) to calculate the climate elasticity over China instead of the *PET* data from the FAO Penman-Monteith method. The related results and some figures and tables have been updated in the revised MS. We believe the new climate elasticity coefficients would be more accurate compared with that in the original version. Meanwhile, the *PET* of GCMs calculated by the Thornthwaite method was corrected by the equation (1) in the revised MS. We compared the corrected *PET* with the *PET* calculated from the Penman method at both basin and grid scales (as shown in Figure 3 in the revised MS). The results indicated the Thornthwaite method corrected by the equation (1) significantly improves the accuracy of *PET* and can be acceptable for the *PET* calculation of the 28 GCMs. For more information please see lines 117-129 in the revised MS. In future work, we are going to compute the Penman *PET* using the meteorological data from the CMIP5 output and make a comparative analysis to fully understand the *PET* calculation uncertainties in the projections of climate change.

Reference:

Harris, I., Jones, P. D., Osborna, T. J., Lister, D. H.: Updated high-resolution grids of monthly climatic observations–the CRU TS3.10 Dataset, Int. J. Climatol., 34(3), 623–642, 2014.

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Anonymous Referee #2：

This paper applies Budyko's concept of 'climate elasticity' in the response of runoff to changes in precipitation, potential evapotranspiration and catchment properties to projections of climate change from an ensemble of general circulation model projections. The authors use this to assess the robustness of projections of changes in future due to climate change in different regions of China.

Climate elasticity concept seems quite neat for the question of responses to climate change (separating P and PET drivers, and also with the potential for accounting for other drivers via the catchment properties) and in my opinion the authors have applied this appropriately to the specific question of responses to an ensemble of climate change projections. I would however advise more care in the interpretation, as these should not be taken as actual predictions of the future (which the language used some- times suggests that there are). There are 3 reasons for this：
1. (1) While the use of the multi-model ensemble probably is a good, well-established way to explore a number of possible outcomes, the ensemble is not designed to be probabilistic, ie: it is not intended to give an indication of likelihoods. It is an 'ensemble of opportunity', using all models that happened to be available in the community, and the levels of skill for regional climate change in China will vary somewhat arbitrarily. The models themselves have not been specifically chosen or varied in order to systematically explore regional climate changes. Likelihood statements generally require further backing-up with understanding of model performance and the simulated climate processes in the region in question. Therefore I would encourage the authors to avoid terms such as "climate change will likely cause an obvious increase (decrease) of R" – the simulations are not intended to give guidance on likelihoods. (2) It is also not clear to me whether the catchment properties term includes plant stomatal responses to CO2. (It could do in theory). Two recent papers (Milly and Dunne, 2016, Nature Climate Change, and Swann et al, 2016, PNAS) showed that projected runoff changes in the GCMs tend to show a greater increase or smaller decrease in runoff than many hydrological models, because the GCM land surface schemes tend to include this term whereas hydrological models do not. It is not clear whether the VIC model includes this here or not. (3) The method used here does not, I believe, include other drivers of hydrological change eg. Land cover change, groundwater and river water extraction, irrigation

etc. I think that in theory the catchment properties quantity could account for this, but it has not been applied to this here. We cannot assume that climate change is the only driver of hydrological change, and hence the interpretation of the results should bear this in mind.

Response: Thank you very much for your nice comments. For the question 1, we quite agree with your points that the multi-model ensemble is not designed to be probabilistic and is not intended to give an indication of likelihoods. Likelihood statements, which generally require further backing-up with understanding of model performance and the simulated climate processes, are not appropriate here. According to your good suggestions, we have changed the statements of some sentences to avoid term such as 'climate change will likely cause an obvious increase (decrease) of *R*' (changed to 'climate change is projected to cause an increase (decrease) in *R*'). For more information please see the red colored text in the revised MS.

For the question 2, thank you for providing these two very nice references (Milly and Dunne, 2016, Swann et al, 2016), which showed a very important information that the plant responses to increasing CO_2 tend to save more water on land, leading to a greater increase in runoff. We note that the VIC model used for the calculation of runoff does not include the schemes with the plant stomatal responses to CO_2. Therefore, under high CO_2 condition, neglecting the plant stomatal responses to CO_2 would lead to a underestimation of runoff in the hydrological model. According to your good comments, we made a discussion on this point to highlight the importance of the plant stomatal responses to CO_2 in the assessment of hydrological impacts of climate change. For more information please see lines 368-372 in the revised MS. In addition, the empirical parameter in the Budyko equations well accounts for the effects of catchment properties (e.g. land surface characteristics, the average slope, and vegetation type) on the water-energy balance. Therefore, the catchment properties term could include plant stomatal responses to CO_2 in theory. This is a very nice suggestion for us to try to characterize the plant stomatal responses to CO_2 using the catchment properties term in the future work, especially under high CO_2 condition.

For the question 3, we quite agree with your comments that there are other drivers of hydrological change in addition to climate change. Our method only considers the hydrological change due to climate change but neglects the effects of the variability of catchment properties (e.g., land cover change, groundwater and river water extraction, urbanization, irrigation, etc.) on the hydrology. According to your good comments, we made a discussion on the other drivers (catchment properties) of hydrological change for the interpretation of the results. For more information please see lines 363-368 in the revised MS.

2. The authors do acknowledge some of these issues to some extent at the end of the paper, but this is after the earlier discussion which often uses language of prediction, which I think goes too far. I would suggest terms such as "Climate change is projected to cause an increase (decrease) in R*: : :*." Also I suggest the authors address the above points in more detail, highlighting the limits to the interpretation of the CMIP5 ensemble in terms of likelihoods.

Response: Thank you very much for your nice comments. According to your good suggestions, we have changed the sentence "climate change will likely cause an obvious increase (decrease) of *R*…" to "climate change is projected to cause an increase (decrease) in *R*…". We also addressed the above points in more detail to highlight the limits to the interpretation of the CMIP5 ensemble in terms of likelihoods. For more information please see the red colored text in the revised MS.

3. My other concern is why the authors chose to use the Thorthwaite method for PET. It is stated on page 14 line 4 that this is because there is a "lack of meteorological data (such as relative humidity) in the GCM data. This is not true – GCMs are meteorological models, and indeed some of the CMIP5 GCMs are used in slightly different variants for numerical weather prediction. A huge range of meteorological outputs is available, including RH – see here

http://cmip-pcmdi.llnl.gov/cmip5/docs/standard_output.pdf.
I recommend that the authors use the data portal http://cmippcmdi.llnl.gov/cmip5/data_description.html at PCMDI, who organised CMIP5. The Canadian Climate Centre webpage used by the authors only has a very limited number of variables.

Response: Thank you very much for your nice comments. In the original version (i.e. initial submitted manuscript), the *PET* of GCM for the baseline 1971–2000 and the future period 2071–2100 is estimated by the Thornthwaite method. We noted that the temperature-based Thornthwaite method is lack of physical basis, and it is necessary to justify the use of the Thornthwaite method and the use of more physically *PET* calculation methods. Thank you very much for informing us the meteorological data used for the *PET* calculation from the CMIP5 output http://cmippcmdi.llnl.gov/cmip5/data_description.html at PCMDI. Indeed, there is a huge range of meteorological outputs (including RH) from the CMIP5 models, which are enough for the calculation of *PET* by the Penman method. However, due to large amounts of data needed to be processed (including (1) download the 28 GCMs meteorological data, (2) statistical downscaling of the 28 GCMs meteorological data over China, (3) bias correction of the 28 GCMs meteorological data, (4) calculations of *PET* for the 28 GCMs, and (5) bias correction of *PET* for the 28 GCMs), so it is difficult for us to complete it in a short period. However, we tried our best to correct the *PET* of GCMs, and made a detailed comparison of the corrected *PET* method with other *PET* calculation methods to justify the use of *PET* calculation of the GCMs. In particular, there are three main changes for the *PET* calculations in the revised MS, which are as follows:

(1) We used a more physically *PET* data that estimated by the Penman equation (data during the period 1960–2008 provided by the Hydroclimatology Group of Princeton University) to calculate the climate elasticity over China instead of the *PET* data from the FAO Penman-Monteith method. We believe the climate elasticity would be more accurate in the revised MS than in the original version.

(2) We used a multiplicative correction method to correct the *PET* data of GCMs calculated from the Thornthwaite method (as shown in equation (1) in the revised MS). Based on the monthly data of temperature covering the period 1960–2008 provided by the Climatic Research Unit (CRU), the *PET* was calculated by the Thornthwaite method and then corrected by the equation (1) to test the applicability of the multiplicative correction method. The results indicated that the corrected annual *PET* shows a good agreement with that calculated by the Penman method (as shown in Figure 3 in revised MS). These two methods are quite consistent at both basin and grid scales, suggesting that the multiplicative correction method is acceptable for the bias correction of *PET* of the GCMs.

(3) We compared the four *PET* calculation methods (i.e., the Penman method, the Thornthwaite method, the FAO-56 Penman–Monteith method, and the Thornthwaite method corrected by the equation (1) in the revised MS) to test the robustness of the *PET* elasticity result subject to *PET* uncertainties. The results indicated that the mean annual *PET* by the Penman method, the FAO-56 Penman–Monteith method, and the Thornthwaite method corrected by the equation (1) are quite consistent, and the *PET* elasticity calculations from these three methods give very similar results in all 14 basins (as shown in Figure 13 in the revised MS). That is to say, the Thornthwaite method corrected by the equation (1) significantly improves the accuracy of *PET* and can be acceptable for the *PET* calculation of the GCMs.

Considering your good suggestions, in the future work we are going to calculate the Penman *PET* using the meteorological data from the CMIP5 output and further make a comparative analysis to fully understand the *PET* calculation uncertainties in the projections of climate change.

Responses of runoff to historical and future climate variability over China

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Abstract. China has suffered some of the effects of global warming, and one of the potential implications of climate warming is the alteration of the temporal-spatial patterns of water resources. Based on the long-term (1960–2008) water budget data and climate projections from 28 Global Climate Models (GCMs) of the Coupled Model Intercomparison Project Phase 5 (CMIP5), this study investigated the responses of runoff (*R*) to historical and future climate variability in China at both grid and catchment scales using the Budyko-based elasticity method. Results show that there is a large spatial variation in precipitation (*P*) elasticity (from 1.1 to 3.2) and potential evaporation (*PET*) elasticity (from -2.2 to -0.1) across China. The *P* elasticity is larger in northeast and western China than in southern China, while the opposite occurs for *PET* elasticity. The catchment properties elasticity of *R* appears to have a strong non-linear relationship with the mean annual aridity index and tends to be more significant in more arid regions. For the period 1960–2008, the climate contribution to *R* ranges from -2.4 % yr^{-1} to 3.6 % yr^{-1} across China, with the negative contribution in northeast China and the positive contribution in western China and some parts of the southwest. The results of climate projections indicate that although there is large uncertainty involved in the 28 GCMs, most project a consistent change in *P* (or *PET*) in China at the annual scale. For the period 2071–2100, the mean annual *P* is projected to increase in most parts of China, especially the western regions, while the mean annual *PET* is projected to increase in all of China, particularly the southern regions. Furthermore, greater increases are projected for higher emission scenarios. Overall, due to climate change, the arid regions and humid regions of China are projected to become wetter and drier in the period 2071–2100, respectively (relative to the baseline 1971–2000).

Key words: Runoff; Budyko hypothesis; climate elasticity; climate variability; CMIP5 GCMs; China

1 Introduction

Climate change has become increasingly significant (IPCC, 2013), and numerous studies have reported that climate warming is likely leading to the alteration of the hydrological cycle (Oki and Kanae, 2006; Jung et al., 2010). The dynamic properties of the hydrological cycle are governed by the interactions and feedbacks between atmospheric and land surface hydrologic processes on a catchment scale. The potential consequences of anthropogenic climate change on the hydrological cycle have received significant attention over the last two decades (Wang et al., 2012; IPCC, 2013).

Runoff (*R*), as a commonly adopted indicator of the hydrologic cycle, is critical to human lives and economic activities (Milly et al., 2005). There is a great deal of previous work exploring the impact of climate variations on *R*, with the motivation stemming from the region's vast resources (Christensen et al., 2004; Guo et al., 2009, Piao et al., 2010; Chen et al., 2012; Harding et al., 2012; Wang et al., 2012; Xu et al., 2013b), dangers of flooding (Kay et al., 2006, 2009, 2012; Raff et al., 2009; Liu et al., 2013; Xiao et al., 2013; Wang et al., 2013; Smith et al., 2014; Wu et al., 2014, 2015), and agricultural water uses (Vano et al., 2010). The most common practices in these previous studies are to use the hydrological models driven by the output from Global Climate Models (GCMs) to simulate the hydrological process (e.g., *R*) under future climate change scenarios. However, the key issue faced by such studies is the need to convert coarse resolution GCM outputs to local catchment-scale climatic variables at a higher spatial resolution to serve as the input to a hydrological model (Vano et al., 2015; Wu et al., 2015). The impact assessments are resource intensive and usually subject to uncertainties related to the choice of hydrological model, GCMs, emissions scenarios, and downscaling techniques (Vano et al., 2014, 2015).

With the uncertainty in *R* due to climate change, simple tools able to provide robust estimates of this impact are essential to support policy and planning decisions. Climate elasticity, as an important indicator, provides a measure of sensitivity of the changes in *R* due to the changes in climate. Schaake (1990) made the first attempt to introduce the concept of elasticity and related the climate elasticity of *R* to precipitation (*P*). Since then numerous climate elasticity methods have been developed for evaluating the hydrologic response to climate change all over the world (Schaake, 1990; Dooge et al., 1999; Sankarasubramanian et al., 2001; Milly and Dunne, 2002; Fu et al., 2007; Zheng et al., 2009; Ma et al., 2010; Yang and Yang, 2011; Yang et al., 2014; Vano et al., 2015). Sankarasubramanian et al. (2001) provided a detailed category of climate elasticity methods for modelling climate change impacts. One of the most common methods is to analytically derive the sensitivity of *R* based on the Budyko hypothesis, due to its clear theory and that it does not rely on a large amount of data (Yang and Yang, 2011). More importantly, the Budyko-based elasticity method can derive the climate elasticity and can also represent the impact of the catchment characteristics through the parameters of the Budyko model. Accordingly, it is widely applied for the assessment of the hydrologic impacts of climate change (Dooge et al., 1999; Zheng et al., 2009; Yang and Yang, 2011; Yang et al., 2014).

China is a vast land, spanning many degrees of latitude with complicated terrain, which results in a large regional variation in climate elasticity. The investigation of the *P* elasticity of *R* has been reported in many regions of China, such as the Miyun

Reservoir basin (Ma et al., 2010), Luan River basin (Xu et al., 2013a), the headwater catchments of the Yellow River basin (Zheng et al., 2009), Poyang Lake basin (Sun et al., 2013), and Hai River and Yellow River basins (Yang and Yang, 2011; Liu and McVicar, 2012). Recently Yang et al. (2014) investigated the climate elasticity of *R* for the 210 catchments of China based on the Budyko-based elasticity approach. The results indicated that the *P* elasticity exhibits a large regional variation, with a small range in southern China, the Songhua River basin and the northwest and a large range in the Hai River basin, the Yellow River basin, and the Liao River basin. Although the aforementioned studies have certainly made advances in understanding the climate elasticity of *R* in China, our knowledge about the responses of *R* to climate change over various temporal and spatial scales remains rather limited due to the large regional variation in climate types and catchment characteristics. The question of how climate change will affect *R* over China in the future is also an important problem to be addressed. Developing a more accurate and quantitative understanding of the changing water resources over various temporal and spatial scales under a changing environment is therefore a high priority for China.

Based on the unique long-term (1960–2008) land surface dataset of China and the climate projections from 28 GCMs of the Coupled Model Intercomparison Project Phase 5 (CMIP5), the objectives of this research are (1) to investigate the changes of *R* and climate variables and their relationship at an interannual scale; (2) to estimate quantitatively the climate elasticity and catchment properties elasticity of *R* across China at both grid and catchment scales; and (3) to predict climate change and the changes in *R* due to future climate change for China from the CMIP5 projections at both grid and catchment scales.

2 Data and methodology

2.1 Data sets

Monthly data of potential evaporation (*PET*) covering the period 1960–2008 over China are provided by the Hydroclimatology Group of Princeton University (Sheffield et al., 2006, 2012). The *PET* is estimated by the Penman equation (Penman, 1948; Shuttleworth, 1993), using the updated meteorological dataset obtained from Sheffield et al. (2006, 2012). A long-term (1960–2008) daily land surface dataset over China, including *P*, surface runoff (*RS*), and baseflow (*BS*), with a 0.25 degree spatial resolution were obtained from the Land Surface Processes and Global Change Research Group (Zhang et al., 2014). In this dataset, *P* is driven by interpolating gauged daily precipitation from 756 meteorological stations of the Chinese Meteorological Administration (CMA). *RS* and *BS* are derived from the Variable Infiltration Capacity (VIC) model forced by the gridded daily climate forcings (i.e. *P*, maximum and minimum temperature, and wind speed). VIC model parameters, including the infiltration shape parameter, the second and third soil layer depths, and the three parameters in the base flow scheme, were estimated by using an optimization algorithm of the multi-objective complex evolution of the University of Arizona (Zhang et al., 2014). The simulated monthly *RS* and *BS* match well with the observations at the large river basins in China (Zhang et al., 2014). Compared with the global product of a similar nature, this dataset provides a more reliable estimate of land surface variables over China (Nijssen et al., 2001; Adamet al., 2006; Rodell et al., 2004; Sheffield et al., 2006; Sheffield and Wood, 2007; Pan et al., 2012). In this study, the data of *P*, *RS*, and *BS* are initially regridded onto 0.5^{o} grids over China using the linear interpolation method. All the daily data (*P*, *RS*, and *BS*) and monthly data (*PET*) are then aggregated temporally for the annual scale over China. The *R* was calculated by the sum of *RS* and *BS* at each of the 0.5^{o} grid points.

Climate projections from 28 CMIP5 GCMs (as shown in Table 1) are provided by the Canadian Climate Data and Scenarios (CCDS, http://www.cccsn.ec.gc.ca/index.php?page=gridded-data). These data, including simulations of surface air temperature (*T*), *P*, sea ice thickness, sea ice concentration, snow depth, and near-surface wind speed, are statistically downscaled and regridded onto a common 1^{o}×1^{o} global grid by the CCDS. In this study, monthly *P* and monthly *T* over China, including one historical simulation for the period 1971–2000 and three emission scenarios (RCP2.6, RCP4.5, and RCP8.5) for the future period 2071–2100 from each of the 28 CMIP5 models and the multi-model ensemble of 28 CMIP5 models, are used for the projections of climate change. The data are initially disaggregated to 0.5^{o} grids over China then corrected by using a 'delta change' method (Wu et al., 2016), on the basis of the observed data of *P* and *T* as provided by the Climatic Research Unit (CRU) of the University of East Anglia (Harris et al., 2014).

Figure 2 shows the comparison of observed mean annual *T* and *P* and the corresponding simulations from 28 CMIP5 models before and after bias correction for the 14 basins in China. The basin number is consistent with that given in Figure 1. As shown, the uncorrected model simulations tend to underestimate *T* and overestimate *P* for most of the basins, with more uncertainties for the simulation of *P* than for *T*. Compared to the uncorrected model results, the bias correction results represent large improvements and show a good agreement with the observed values for these basins. Therefore, the bias correction model simulations are acceptable for the investigation of climate change projections in this study.

From the GCM data, the *PET* for the periods 1971–2000 and 2071–2100 under different emission scenarios are initially estimated by the Thornthwaite method (Thornthwaite, 1948) and then corrected by a multiplicative bias correction method as follows:

$$PET_{cor,GCM,i} = PET_{Th,GCM,i} \times \frac{\overline{PET}_{Pen,obs,i}}{\overline{PET}_{Th,obs,i}} \quad (1)$$

where $PET_{cor,GCM,i}$ and $PET_{Th,GCM,i}$ are bias-corrected annual *PET* and the *PET* calculated from the Thornthwaite method, respectively, for the *i*th grid point of the GCMs. $\overline{PET}_{Pen,obs,i}$ and $\overline{PET}_{Th,obs,i}$ are the 49-year (1960–2008) averages of

PET calculated from the Penman and Thornthwaite methods, respectively, for the *i*th grid point.

Based on the *T* data from the CRU, the Thornthwaite method is used to calculate *PET* to test the applicability of Equation (1). Figure 3 shows a comparison of annual *PET* calculated from the Penman method and that from the Thornthwaite method corrected by Equation (1) during the period 1960–2008. It is clear that the corrected *PET* agrees well with the *PET* from the Penman method, with the correlation coefficients of 0.94 and 0.958 at the catchment and grid scales, respectively. This suggests that Equation (1) can be acceptable for the bias correction of *PET* in the GCMs.

2.2 Sensitivity of runoff to climate and catchment properties

The Budyko framework has been widely used to study basin-scale water and energy balances. Two of the one-parameter formulations of the Budyko curve proposed by Choudhury (1999) (Equation (2), see also Yang et al., 2008) and Fu (1981) (Equation (3), see also Zhang et al., 2004) are expressed as:

$$E = P\frac{PET}{(P^n + PET^n)^{1/n}}, \quad n \in (0, \infty) \tag{2}$$

$$E = P + PET - (P^\omega + PET^\omega)^{1/\omega}, \ \omega \in (1, \infty) \tag{3}$$

where n and ω are empirical parameters, representing the effects of other factors (e.g. land surface characteristics, the average slope, vegetation type or land use, and climate seasonality) on the water-energy balance (Yang et al., 2008, 2014; Roderick and Farquhar, 2011; Li et al., 2013a). Yang et al. (2008) calibrated the parameters n and ω using long-term water balance data from 108 catchments from the nonhumid regions of China and found that these two empirical parameters are linearly correlated.

Based on the Budyko hypothesis and assuming steady state conditions, Roderick et al. (2011) and Yang and Yang (2011) derived the elasticity method to estimate the contribution to *R* from the changes in climate (represented by *P* and *PET*) and catchment properties as follows:

$$\frac{dR}{R} = \varepsilon_P \cdot \frac{dP}{P} + \varepsilon_{PET} \cdot \frac{dPET}{PET} + \varepsilon_n \cdot \frac{dn}{n} \tag{4}$$

where $\varepsilon_P, \varepsilon_{PET}$, and ε_n represent the elasticity coefficients of *P*, *PET*, and catchment properties respectively, and are expressed as:

$$\varepsilon_P = \frac{P}{R}(1 - \frac{\partial E}{\partial P}) \tag{5a}$$

$$\varepsilon_{PET} = -\frac{PET}{R}\frac{\partial E}{\partial PET} \quad (5b)$$

$$\varepsilon_n = -\frac{n}{R}\frac{\partial E}{\partial n} \quad (5c)$$

where $\frac{\partial E}{\partial P}$, $\frac{\partial E}{\partial PET}$, and $\frac{\partial E}{\partial n}$ denote the first order partial derivatives of the Budyko equation with respect to *P*, *PET*, and the parameter *n*. In this study, both Equations (2) and (3) are used for the estimation of the elasticity of *P*, *PET*, and catchment properties over China.

2.3 Trend estimate method

The Mann-Kendall (M-K) nonparametric test (Mann, 1945; Kendall, 1975) is an effective tool for detecting the statistical significance of trends in the time series of meteorological and hydrological variables (Yang et al., 2014; Wu and Huang, 2015). In this study, the M-K method is used to detect the significance of monotonic trends in hydroclimatic time series. The nonparametric trend slope estimator developed by Sen (1968) is used for the magnitude estimation of the trends in a hydroclimatic time series.

3 Results

3.1 Interannual variability of climatic variables and runoff

The standard deviations for annual *P*, *PET*, and *R* are computed for each of the 0.5^{o} grids in China, and the *PET* deviation ratio (σ_{PET}/σ_P) and the *R* deviation ratio (σ_R/σ_P) are calculated. The spatial distributions of *PET* deviation ratio and *R* deviation ratio across China are displayed in Figure 4(a) and (b). As shown, the *PET* deviation ratio is rather small in most parts of China, especially the southern regions, while a larger value is observed mainly in the Xinjiang region, where there are greater aridity indices. Generally, atmospheric water is enough to accommodate the limited *PET* in humid climates, which would lead to a limited response of *PET* to *P* variability. Specifically, the interannual variability of *PET* is more sensitive to that of *P* in arid climates (with water limits) than in humid climates (with energy limits). In contrast to the *PET* deviation ratio, the *R* deviation ratio tends to increase from arid climates to humid climates. The reason for this is that, in arid climates, the catchment water supply is very limited and gives priority to evaporation and soil storage capability, which leads to little variation in *R*.

Figure 4(c) shows the relationship between the *R* deviation ratio and mean annual aridity index ($\overline{\phi}$) for all 0.5^{o} grids in China. As indicated, $\overline{\phi}$ is a major control for the *R* deviation ratio under not very dry conditions (e.g. $\overline{\phi}$ <10); that is, the *R* deviation ratio decreases with increased $\bar{\phi}$. However, under very dry conditions (e.g. $\bar{\phi}$>10) the *R* deviation ratio becomes insensitive to $\bar{\phi}$, since in this case, other factors, such as soil storage capacity, can also have a large impact on the variation of *R*.

3.2 Sensitivity of runoff to climate and catchment properties

3.2.1 Climate elasticity

The *P* elasticity and *PET* elasticity of *R* based on Equations (2) and (3) are estimated at each of the 0.5^{o} grids in China. As shown in Figure 5, the spatial patterns of *P* elasticity and *PET* elasticity from Equations (2) and (3) are almost the same in all regions of China. There is a large spatial variation in *P* elasticity and *PET* elasticity, i.e. ranging from 1.1 to 3.2 and from -2.2 to -0.1 across China, respectively. In particular, *P* elasticity is more significant in the northeast and western areas than in southern China, which is in contrast to *PET* elasticity. Figure 6 shows the relationship between $\bar{\phi}$ and climate (*P* and *PET*) elasticity. As shown, the *P* (*PET*) elasticity first increases (decreases) and then decreases (increases) with the increase of $\bar{\phi}$ under not very dry conditions (i.e. $\bar{\phi}$<10). However, when $\bar{\phi}$ becomes large enough (e.g. $\bar{\phi}$>10), both *P* and *PET* elasticity becomes insensitive to $\bar{\phi}$.

The climate elasticity estimated for each of the 14 large basins is shown in Table 2. The values of *P* elasticity are in the range of 1.39–2.28, with a larger (~smaller) elasticity in the Haihe River and Inner Mongolia River (Southwest Drainage). A similar phenomenon is found for *PET* elasticity, which suggests that Haihe River (Southwest Drainage) is the most (least) sensitive to *PET* among the 14 basins. Overall the values of *P* elasticity and *PET* elasticity derived by Equation (2) are very close to those from Equation (3), but the difference between them tends to be larger for dry basins with increasing aridity indices.

By using the estimates of climate elasticity derived by Equation (2), the change in *R* as a function of the percentage change in *P* and *PET* is calculated for the 14 basins (Figure 7). The *R* is positively related to *P* and negatively related to *PET*, and the magnitudes and patterns of the response of *R* to changes in *P* and *PET* vary in different scales. Generally, the *R* is more sensitive to climate in the Haihe River and Inner Mongolia River, while relatively weak sensitivity is found in the Southwest Drainage and Yangtze.

3.2.2 Catchment properties elasticity

The spatial distributions of catchment properties elasticity from Equations (2) and (3) are displayed in Figure 5(e) and (f). As shown, the catchment properties elasticities for these two equations are rather similar across China, and the values of Equation (3) are generally smaller than those from Equation (2). Regarding the spatial pattern, the catchment properties elasticity is very weak (approximately equal to 0) in southern China and some regions of northeast China, but it tends to be more significant in some water-limited regions of northwest China. Figure 6(c) shows the relationship between $\bar{\phi}$ and the parameter elasticity for all 0.5^{o} grids in China. It suggests that $\bar{\phi}$ is a major control for catchment properties elasticity across China, i.e. the catchment properties elasticity would become stronger with increasing aridity indices. The catchment properties elasticities estimated for the 14 large basins are shown in Table 2. The catchment properties elasticity shows a large spatial variation, ranging from -2.78 to -0.24 for Equation (2) and from -4.3 to -0.33 for Equation (3). Overall, the changes in *R* are more sensitive to catchment properties in arid basins with larger aridity indices, which is consistent with the findings at the grid scale.

3.3 Climate change during 1960–2008

The annual trend magnitudes in *P*, *R*, *PET*, and aridity index during the period 1960–2008 are shown in Figure 8 (a), (b), (c), and (d). As indicated, both *P* and *R* show an increasing trend mainly in the northwest and southeast regions and a decreasing trend mainly in the central region and North China plain. A significant increasing in *PET* is detected mainly in northeast China and eastern China, while the decreases mainly occur in most parts of western China. The aridity index tends to show an increasing trend in most parts of China, indicating an increasing risk of meteorological drought in these regions during the past several decades. In contrast, the decrease of aridity index is only found in some parts of western China.

3.4 Changes in runoff due to climate change during 1960–2008

Using the estimates of climate elasticity from Equation (2), the contributions of *P*, *PET*, and climate (i.e. *P*& *PET*) to *R* in China for the period 1960–2008 are calculated (as shown in Figure 8(e), (f), and (g)). A positive contribution (up to 3.7 % yr^{-1}) from *P* to *R* is mainly recorded in western China, while a negative contribution is found mainly in northeast China and North China plain. Negative and positive contributions of *PET* to *R* mainly occur in northeast China and western China, respectively. The contributions of climate, i.e. the sum of the contributions from *P* and *PET*, ranges from -2.4 % yr^{-1} to 3.6 % yr^{-1} across China. The spatial pattern of climate is rather similar to that of *P*, showing a negative contribution in northeast China and a positive contribution in western China and some parts of the southeast. Particularly, the largest positive contribution of climate occurs in the Tibetan plateau. The contributions of *P*, *PET*, and climate (i.e. *P*& *PET*) to *R* in the 14 river basins for the period 1960–2008 are shown in Table 3. A positive contribution of *P* is detected in Southeast Drainage, Southwest Drainage, Qiangtang, Qinghai, Xinjiang and Hexi, while an oppoiste contribution is found in other basins. In contrast, a negative contribution of *PET* is found in most of the basins (except for Qiangtang and Hexi). In general, there is an increased *R* in Southeast Drainage, Southwest Drainage, Qiangtang, Qinghai, Xinjiang and Hexi (from 0.06 to 1 % yr^{-1}) and a decreased *R* in other basins (from -1.12 to -0.12 % yr^{-1}).

3.5 Future climate change

Figure 9 shows the uncertainty range of the relative change in mean annual *P* and *PET* in the basins for the period 2071–2100 under the RCP2.6, RCP4.5, and RCP8.5 scenarios as predicted by 28 CMIP5 models (relative to the baseline 1971–2000). As shown, there is a large difference between different GCMs and emission scenarios, which highlights the uncertainty inherent in projections of climate change. However, overall *P* is projected to increase in most of the basins, and greater increases are projected for higher emission scenarios. Meanwhile, greater increases tend to be projected for more arid basins, suggesting a decreasing risk of meteorological drought in the future. The average changes (red dotted lines) of mean annual *P* for the 14 basins range from 2.4 % to 11.0 % in RCP2.6, from 4.2 % to 16.0 % in RCP4.5, and from 3.1 % to 23.7 % in RCP8.5. The largest increase in the RCP2.6 and RCP8.5 scenarios is found for the Qinghai River, while the largest increase in the RCP4.5 scenario is projected for the Hexi River. For *PET*, there is an increase projected in all basins due to climate warming, with the largest and smallest increases in the RCP8.5 and RCP2.6 scenarios, respectively. However, a large uncertainty exists among the GCMs, which is similar to that for *P*. Furthermore, the uncertainty range tends to be larger with higher emission scenarios. The average changes (red dotted lines) of *PET* for the basins range from 7.0 % to 12.0 % in RCP2.6, from 13.5 % to 22.2 % in RCP4.5, and from 27.9 % to 49.8 % in RCP8.5. The largest and smallest average increases are projected for the Pearl River and Qiangtang River, respectively.

Figure 10 displays the multi-model ensemble median relative change in mean annual *P* and *PET* in China for the period 2071–2100 (relative to the baseline 1971–2000). The projected changes in *P* (or *PET*) have a similar spatial pattern for the three emission scenarios; that is, *P* is projected to show an increase in western China and the northeast, and *PET* is projected to increase significantly in southern China and some parts of the Tibetan plateau, especially for the RCP8.5 scenario. In addition, note that there are small changes in *P* and significant increases in *PET* projected for southern China. This would result in an increasing risk of meteorological drought in the future.

3.6 Future changes in runoff due to climate change

Based on the estimates of elasticity from Equation (2), the percentage changes in the contributions of annual *P* and *PET*, as well as climate, to *R* from the 28 GCMs for the period 2071–2100 are calculated for each of the 14 basins (relative to the baseline 1971–2000). As shown in Figure 11, the changes in *P* contribution mainly follow the changes in *P* (Figure 9). A positive contribution from P is projected for most of the basins, and larger contributions occur in more arid basins, as well as in higher emission scenarios. Negative contributions of PET to R are projected for all basins due to the negative coefficients of PET elasticity. Smaller contributions of PET are mainly found in the Southwest Drainage. In contrast, larger contributions are projected mainly in the Huaihe River, Haihe River, and Inner Mongolia River, where the percentage decreases from the 28 models can be up to 25 %, 35 %, and 90 % in the RCP2.6, RCP4.5 and RCP8.5 scenarios, respectively.

Climate change is projected to reduce the R in some humid basins, such as the Southeast Drainage and Pearl River, where the average changes in the three emission scenarios range from -22.83 % to -3.0 % and from -23.6 % to -3.5 %, respectively (Figure 11 (g), (h) and (i)). For other basins, particularly for arid basins, the R is projected to increase due to climate change. The largest average changes in R under the RCP2.6 and RCP4.5 scenarios are found in the Qinghai River (12.85 % and 16.18 %, respectively). For the RCP8.5 scenario, they are found in the Qiangtang River (18.59 %). Note that there is an obvious decrease in R (-17.59 %) projected for the Huaihe River under RCP8.5 scenario, which is mainly caused by the larger negative contribution of PET.

Figure 12 shows the spatial distributions of the relative changes in the contributions of annual P and PET as well as climate to R in China for 2071–2100. This is based on the CMIP5 multi-model ensemble medians. Compared with the baseline 1971–2000, the increases in R due to the changes in P are projected in western China and some parts of northern China, and this phenomenon is particularly significant in the RCP8.5 scenario (up to 60.3 %). In contrast, the changes in PET are projected to reduce the R in all of China, with the larger decreases occurring mainly in the North China plain, northeast, and some parts of western China. Overall, climate change is projected to cause an obvious increase (decrease) of R in western China (southern China) under any emission scenario (Figure 12(g), (h) and (i)). This suggests that the arid regions (humid regions) in China will become wetter (drier) in the future.

4 Discussion

4.1 The estimation of elasticity

The Budyko-based elasticity method is applied to quantify sensitivity of runoff to climate and catchment properties across China. Two Budyko models proposed by Choudhury (1999) and Fu (1981) are used for the comparison of the estimation of the climate elasticity of R. The results suggest that the climate elasticity is insensitive to the Budyko equations. The climate elasticity of R has been estimated in many regions of China. For example, the values of P elasticity are estimated as 2.4 for the Miyun Reservoir basin (Ma et al., 2010), 2.6 for the Luan River basin (Xu et al., 2013a), 2.1 for the headwater catchments of the Yellow River basin (Zheng et al., 2009), 1.4–1.7 for the Poyang Lake basin (Sun et al., 2013), 1.7–3.1 for the Hai River basin (Xu et al., 2014), 1.1–2.0 for southern China, the Songhua River basin, and the northwest, 2.1–4.8 for the Hai River basin, the Yellow River basin, and the Liao River basin (Yang et al., 2014), and 1.6–3.8 for the 63 catchments of China (Yang and Yang, 2011). In addition, the *PET* elasticity is estimated as -1.04 for the headwater catchments of the Yellow River basin (Zheng et al., 2009) and from -1 to -0.2 for the Poyang Lake basin (Sun et al., 2013). Those results are close to our results for *P* elasticity ranging from 1.1 to 3.2, and for *PET* elasticity ranging from -2.2 to -0.1 in China. It is worth noting that the values of *P* elasticity tend to be larger in the northeast and some parts of western China that are located in arid climates. This is in good agreement with the findings by Sankarasubramanian et al. (2001), which indicated that a larger *P* elasticity occurs in more arid regions. However, some parts of Xinjiang, which is more arid than southern China, have smaller *P* elasticity. Meanwhile, some parts of southern China, which is more humid than other regions in China, have larger *P* elasticity (Figure 5). In addition, the Haihe River basin, located in less arid climates than that of the northwest, shows the largest *P* elasticity in China (Table 2). A similar phenomenon is also introduced in Yang et al. (2014). One of the major reasons for this difference may be attributed to the impacts of human activities that alter the patterns of *R* in these regions. In addition, uncertainties in water budget data, such as the errors in the simulation of *R* and in the estimation of *PET*, may also contribute to this difference.

The comparisons for the estimates of ε_n and ε_ω suggest that although the values of ε_n and ε_ω are mainly dependent on the parameters of Budyko models, the spatial pattern of ε_n is consistent with that of ε_ω at the 0.5^{o} grid points over China (Figure 5(e) and (f)). Yang et al. (2008) indicated that the parameters n and ω from Equations (2) and (3) are linearly correlated. We also conducted a regression analysis of ε_n and ε_ω for all 0.5^{o} grid points over China and found a strong linear correlation between ε_n and ε_ω ($\varepsilon_\omega = 1.7061\varepsilon_n + 0.0986$, $r^2 = 0.96$). In addition, our results show that *R* is more sensitive to catchment properties (ε_n and ε_ω) in the more arid regions (Figure 5(e) and (f)). The possible internal connection is that the arid regions with less vegetation coverage and stronger evaporation do not effectively hold the rainfall water that will be evaporated, leading to the smaller proportion of rainfall for *R*.

4.2 Sensitivity analysis for *PET* calculation methods

We compare four *PET* calculation methods, including the Penman method, the Thornthwaite method, the FAO-56 Penman–Monteith method (Allen et al., 1998), and the Thornthwaite method corrected by Equation (1), to test the robustness of the *PET* elasticity result subject to *PET* uncertainties. In terms of mean annual *PET* as shown in Figure 13 (a), the Thornthwaite method gives relatively low *PET* among the four methods, especially in arid basins (e.g., Qiangtang, Qinghai, Xinjiang and Hexi). This is in agreement with previous studies, which indicated that the Thornthwaite method tends to underestimate *PET* in the arid areas (Hashemi and Habibian, 1979; Malek 1987; Garcia et al., 2004). In contrast, the mean annual *PET* by the other three methods are quite consistent, especially for the Penman method and the Thornthwaite method corrected by Equation (1). A similar result was also reported by Zeng and Cai (2016), which indicated that estimations of water balance at both annual and month scales are generally robust under various *PET* calculation methods (not including the Thornthwaite method). The *PET* elasticity calculations from the four different *PET* data for the 14 river basins are shown in Figure 13(b). The Thornthwaite method yields stronger *PET* elasticity than other three methods in most of the basins mainly due to the underestimation of *PET*. However, the other three methods give very similar results in all 14 basins. In summary, the estimation of *PET* elasticity is robust to the *PET* calculations from the Penman method, the FAO-56 Penman–Monteith method, and the Thornthwaite method corrected by Equation (1), but is not acceptable for the Thornthwaite method.

In general, the Thornthwaite method corrected by Equation (1) significantly improves the accuracy of *PET* (Figure 3 and Figure 13(a)). However, it should be emphasized that the Thornthwaite method is an empirical equation that neglects the effects of atmospheric conditions, such as wind speed, humidity and radiation (McVicar et al., 2012). In addition, the Equation (1) used for the bias correction of *PET* belongs to a 'delta method' (Graham et al., 2007; Sperna Weiland et al., 2010), which only considers the average change but ignores the differences in the standard deviation and the coefficient of variation between the projection and baseline periods (Watanabe et al., 2012). Therefore, a more physically-based *PET* calculation method (such as the Penman method) needs to be considered in the GCMs to fully understand the *PET* calculation uncertainties in the projections of climate change.

4.3 The projections of climate change and runoff

The hydrological impacts of climate change have been investigated in many regions of China, such as the Hanjiang basin (Chen et al., 2007; Guo et al., 2009), the catchment of the Loess Plateau (Wang et al., 2013), the Qingjiang River basin (Chen et al., 2012), the Qiantang River basin (Xu et al., 2013b), the Songhuajiang River basin (Su et al., 2015), the southeastern Tibetan Plateau (Li et al., 2013b), the Pearl River basin (Yan et al., 2015), the Xin River basin (Zhang et al., 2016), the sub-catchments of the Yangtze and Yellow River basins (Xu et al., 2011), the Huang-Huai-Hai region (Lu et al., 2012), and ten major river basins in China (Wang et al., 2012). There is a large uncertainty involved in these impact studies, which results in a large difference in climate projections. For example, Wang et al. (2012) indicated that the prevailing pattern of "north dry and south wet" in China will likely be exacerbated under future climate warming. However, the results of most GCMs in this study suggest that the arid regions and humid regions of China are projected to become wetter and drier in the future, respectively. The main difference between the two studies is the use of different climate models, emission scenarios, and time periods. This also demonstrates that the results of climate projections should be taken with caution, since the regional climate simulations (especially of precipitation) from the GCMs are still not robust at the present stage.

This study focuses on the hydrological change due to climate change (i.e., changes in *P* and *PET*), while the effects of the variability of catchment properties (e.g., land cover change, groundwater and river water extraction, urbanization, irrigation, etc.) on the hydrology are overlooked here. Most of the available GCMs lack of key regional feedback processes involving land use, such as forest plantations, irrigation, and urbanization feedbacks that are critically important throughout China (Piao et al., 2010). The projected changes in catchment properties therefore need to be involved in the GCMs to account for their hydrological impacts. In addition, recent studies indicated that plant responses to increasing CO_2 tend to keep more water on land, therefore resulting in a greater increase in *R* (Milly and Dunne, 2016; Swann et al, 2016). That is to say, the hydrological models (e.g., VIC model), without the schemes of the plant stomatal responses to CO_2, would lead to an underestimation of *R* under high CO_2. Therefore, the implications of plants needing less water under high CO_2 should be included in the assessment of hydrological impacts of climate change.

4.4 Uncertainties

Generally, a multitude of sources of uncertainty are involved in the impact assessment of climate change. In this study, uncertainty mainly comes from the GCMs, emission scenarios, the elasticity method, and the estimation error of the water budget data. To highlight the uncertainty from the GCMs, the 28 GCMs as produced by different research institutes around the world, are used for the comparison of climate change projections. There exists a large difference in the projections of *P* and *PET* among the 28 GCMs. Particularly, the uncertainty range of *P* tends to be larger for more arid regions, while the uncertainty range of *PET* tends to be larger for more humid regions (Figure 9). This highlights the impact of potential misleading conclusions if only one climate model were to be used for the impact assessments. The large uncertainty driven by the GCMs in relation to the hydrological impacts of climate change has been reported in many previous studies (Kay et al., 2009; Prudhomme and Davies, 2009; Chen et al., 2011; Teng et al., 2012; Liu et al., 2013; Wu et al., 2014, 2015). It is worth noting that although the projected ranges of *P* and *PET* show large variability in various GCMs, most project a consistent change (i.e. increase) in *P* and *PET* for the future period (Figure 9). In contrast, the uncertainty from the emission scenarios is smaller than that from the GCMs, since the projected changes in *P* (or *PET*) show a similar pattern under all emission scenarios (Figure 9). The main difference is that the projected changes tend to be more significant in higher emission scenarios.

The elasticity equation (i.e. Equation (4)) used in this study is driven from the linear approximation of the Budyko equation (Equations (2) and (3)) by neglecting the higher order. Such approximation would possibly lead to an uncertainty in the estimation of climate elasticity. Yang et al. (2014) indicated that the error in estimation of elasticity tends to increase with increasing changes in *P* and *PET*, as well as the increased parameter of the Budyko equation. Future research is needed to quantify the effects of the errors on the estimation of elasticity under various climate conditions.

In addition to uncertainty in *PET* calculation (as discussed in section 4.2), there are also uncertainties associated with the estimates of other water budget components, such as *R*. As shown in Figure 14, the sensitivity of climate (i.e., *P* and *PET*) elasticity to *R* varies considerably between basins and tends to be larger in more humid basins. Moreover, *PET* elasticity is more sensitive to changes in *R* compared with *P* elasticity for all 14 basins. As indicated by Zhang et al. (2014), although the *R* is realistically estimated for most of the basins (especially for humid basins) in China with a small relative error, there is still a large relative error for few arid basins in western China due to the lack of meteorological observations. Therefore, the large errors in simulated *R* of the VIC model may result in large uncertainties in elasticity calculation, particularly in western China. Also note that some other natural water sources, such as snow and glaciers, which may contribute to *R*, are overlooked in this study. Lute and Abatzoglou (2014) highlighted the importance of extreme snowfall events in shaping the interannual variability of the water balance. The melting of snow and glaciers is generally significant at a seasonal time scale in some high altitude regions of China. Neglecting the effects of snow and glaciers would lead to a bias in the modelling of *R* for these regions.

5 Conclusion

In this study, the Budyko-based elasticity method was used to investigate the responses of runoff to historical and future climate variability over China at both grid and catchment scales. The climate and catchment properties elasticities of runoff were estimated based on the long-term (1960–2008) land surface data from Zhang et al. (2014). Twenty-eight GCMs with three emission scenarios from the CMIP5 were collected for the projections of climate change and its contribution to runoff in China during the period 2071–2100. The uncertainties associated with the estimates of *PET*, *R*, climate elasticity, as well as climate projections, are discussed in detail. The main findings are summarised as follows:

(1) The interannual variability of *PET* is more sensitive to that of *P* in more arid regions, while the opposite occurs in the response of interannual variability of *R* to that of *P*. A large spatial variation exists in *P* elasticity (from 1.1 to 3.2) and *PET* elasticity (from -2.2 to -0.1) across China. The *P* elasticity is larger in northeast and western China than in southern China, which is opposite to that of *PET* elasticity. Among the 14 river basins, the Haihe River and Southwest Drainage have the largest and smallest climate elasticities, respectively. The catchment properties elasticity of *R* is sensitive to mean annual aridity indices and tends to be stronger in more arid regions with increasing aridity indices.

(2) For the period 1960–2008, the positive (negative) contributions from *P* to *R* are mainly found in western China (northeast China and North China plain), and the positive (negative) contributions of *PET* mainly occur in western China (northeast China). Overall, the climate contribution to *R* ranges from -2.4 % yr^{-1} to 3.6 % yr^{-1} across China during the period 1960–2008, with a negative contribution in northeast China and a positive contribution in western China and some parts of the southwest. The largest positive and negative contributions of climate occur in the Qiangtang and Haihe River basins, respectively.

(3) There is a large uncertainty in climate projections among the 28 GCMs. Moreover, the uncertainty range of the *P* (*PET)* projection tends to be larger for more arid (humid) regions. However, most of the GCMs project a consistent change in annual *P* or annual *PET*. For the period 2071–2100, the *P* is projected to increase in most parts of China, especially the western regions, and the *PET* is projected to increase in all of China, particularly the southern regions. Furthermore, greater increases are projected for higher emission scenarios. Due to future climate warming, the arid regions and humid regions of China are projected to become wetter and drier in the period 2071–2100, respectively (relative to the baseline 1971–2000).

The results of this study (especially of the climate change projections) should be taken with caution, since uncertainties in the results exist because of several issues, including the different simulations of GCMs, the estimation error of climate elasticity, and the estimation error in the water budget components. A thorough investigation of the uncertainty involved in the hydrologic effects of climate change in China should be considered in future research.

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Table 1. CMIP5 GCMs used in this study

No.	Model	Institution (Country)	Resolution
1	BCC-CSM1-1	Beijing Climate Center, China Meteorological Administration, China	1°×1°
2	BCC-CSM1-1-m		
3	BNU-ESM	College of Global Change and Earth System Science, Beijing Normal University, China	1°×1°
4	CCSM4	National Center for Atmospheric Research, USA	1°×1°
5	CESM1-CAM5	Community Earth System Model Contributors, USA	1°×1°
6	CNRM-CM5	Centre National de Recherches Météorologiques / Centre Européen de Recherche et Formation Avancée en Calcul Scientifique, France	1°×1°
7	CSIRO-Mk3-6-0	Commonwealth Scientific and Industrial Research Organization in collaboration with Queensland Climate Change Centre of Excellence, Australia	1°×1°
8	CanESM2	Canadian Centre for Climate Modelling and Analysis, Canada	1°×1°
9	EC-EARTH	EC-EARTH consortium	1°×1°
10	FGOALS-g2	LASG, Institute of Atmospheric Physics, Chinese Academy of Sciences and CESS, Tsinghua University, China	1°×1°
11	FIO-ESM	The First Institute of Oceanography, SOA, China	1°×1°
12	GFDL-CM3	NOAA Geophysical Fluid Dynamics Laboratory, USA	1°×1°
13	GFDL-ESM2G		
14	GFDL-ESM2M		
15	GISS-E2-H	NASA Goddard Institute for Space Studies, USA	1°×1°
16	GISS-E2-R		
17	HadGEM2-AO	National Institute of Meteorological Research/Korea Meteorological Administration, South Korea	1°×1°
18	HadGEM2-ES	Met Office Hadley Centre (additional HadGEM2-ES realizations contributed by Instituto Nacional de Pesquisas Espaciais), UK	1°×1°
19	IPSL-CM5A-LR	Institut Pierre-Simon Laplace, France	1°×1°
20	IPSL-CM5A-MR		
21	MIROC-ESM	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies, Japan	1°×1°
22	MIROC-ESM-CHEM		
23	MIROC5	Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology, Japan	1°×1°
24	MPI-ESM-LR	Max-Planck-Institut für Meteorologie (Max Planck Institute for Meteorology), Germany	1°×1°
25	MPI-ESM-MR		
26	MRI-CGCM3	Meteorological Research Institute, Japan	1°×1°
27	NorESM1-M	Norwegian Climate Centre, Norway	1°×1°
28	NorESM1-ME		

Table 2. The estimations of P elasticity, PET elasticity, and catchment properties elasticity of R in the 14 river basins of China based on Equations (2) and (3). The basin number is consistent with that given in Figure 1. The numbers in the parentheses indicate the 1960–2008 mean aridity index.

Basin No.	ε_P		ε_{PET}		ε_n or ε_ω	
	Eq.(2)	Eq.(3)	Eq.(2)	Eq.(3)	Eq.(2)	Eq.(3)
1 (0.52)	1.64	1.65	-0.64	-0.65	-0.24	-0.33
2 (0.64)	1.63	1.64	-0.62	-0.63	-0.41	-0.61
3 (0.81)	1.55	1.56	-0.55	-0.55	-0.57	-0.93
4 (1.19)	1.40	1.39	-0.40	-0.39	-0.73	-1.44
5 (1.19)	2.09	2.08	-1.08	-1.07	-1.03	-1.47
6 (1.43)	2.06	2.04	-1.05	-1.02	-1.25	-1.83
7 (1.71)	1.92	1.88	-0.91	-0.87	-1.35	-2.10
8 (2.14)	2.28	2.21	-1.29	-1.22	-1.89	-2.70
9 (2.38)	1.78	1.72	-0.79	-0.73	-1.53	-2.54
10 (4.41)	2.23	2.11	-1.22	-1.10	-2.78	-4.16
11 (4.70)	1.81	1.72	-0.82	-0.72	-2.17	-3.67
12 (6.68)	1.72	1.62	-0.73	-0.63	-2.28	-4.08
13 (8.09)	1.66	1.56	-0.65	-0.55	-2.26	-4.27
14 (8.63)	1.63	1.53	-0.64	-0.54	-2.26	-4.30

Table 3. The contributions of P, PET, and climate (i.e. P& PET) to R in the 14 basins of China for the period 1960–2008. The basin number is consistent with that given in Figure 1. The numbers in the parentheses indicate the 1960–2008 mean aridity index.

Basin No.	P (%/a)	PET (%/a)	P&PET (%/a)
1 (0.52)	0.19	-0.13	0.06
2 (0.64)	-0.03	-0.09	-0.12
3 (0.81)	-0.07	-0.07	-0.14
4 (1.19)	0.14	-0.01	0.13
5 (1.19)	-0.18	-0.27	-0.45
6 (1.43)	-0.35	-0.31	-0.66
7 (1.71)	-0.57	-0.34	-0.91
8 (2.14)	-0.74	-0.38	-1.12
9 (2.38)	-0.38	-0.04	-0.42
10 (4.41)	-0.40	-0.26	-0.66
11 (4.70)	0.99	0.01	1.00
12 (6.68)	0.43	-0.01	0.42
13 (8.09)	0.84	-0.02	0.82
14 (8.63)	0.11	0.08	0.19

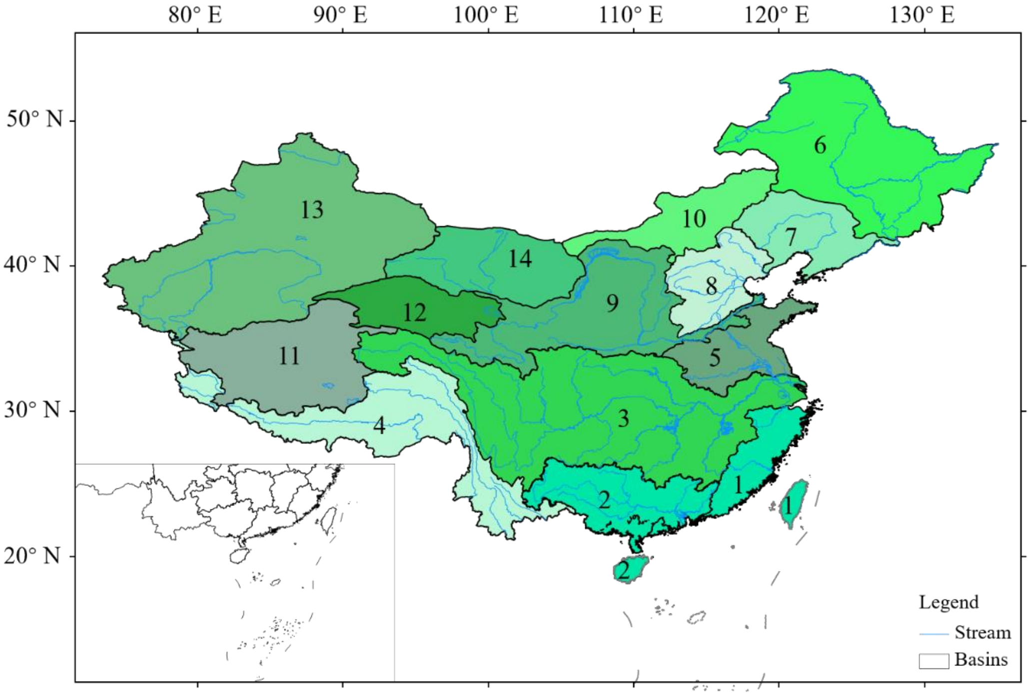

Figure 1. Location of the main river basins in China. The numbers denote the river basins with increasing aridity index: 1, Southeast Drainage (0.52); 2, Pearl River (0.64); 3, Yangtze River (0.81); 4, Southwest Drainage (1.19); 5, Huaihe River (1.19); 6, Heilongjiang River (1.43); 7, Liaohe River (1.71); 8, Haihe River (2.14); 9, Yellow River (2.38); 10, Inner Mongolia River (4.41); 11, Qiangtang River (4.70); 12, Qinghai River (6.68); 13, Xinjiang River (8.09), 14, Hexi River (8.63). The numbers in the parentheses indicate the 1960–2008 mean aridity index.

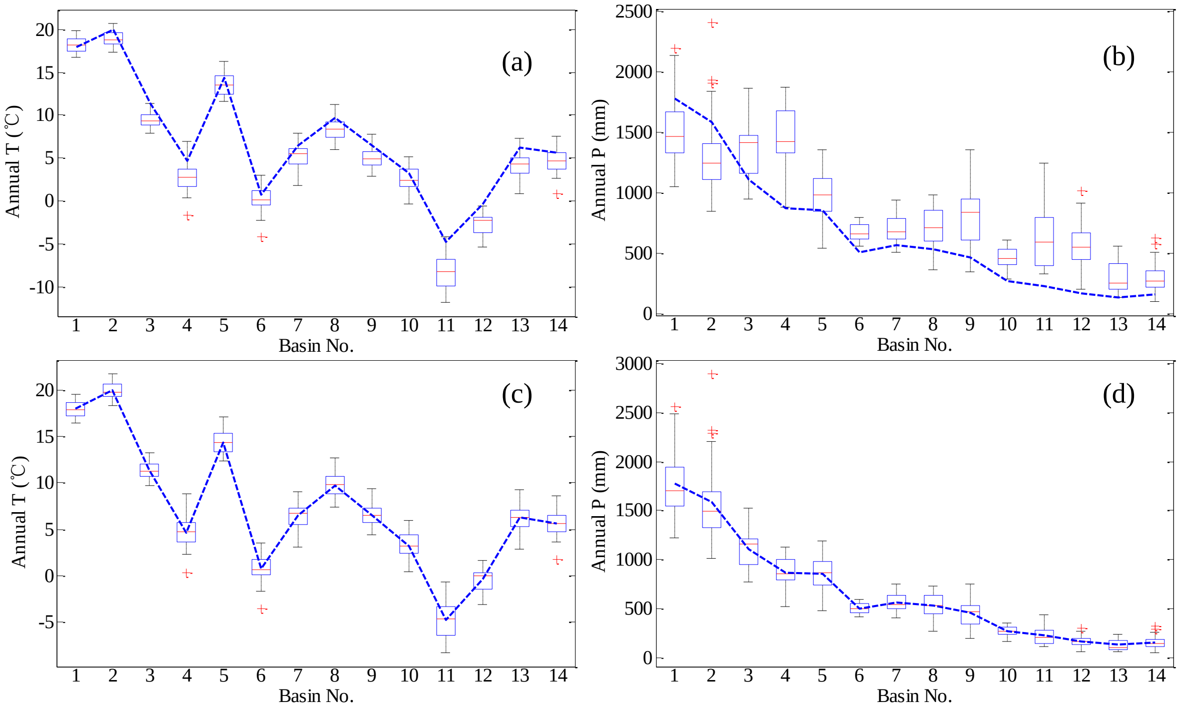

Figure 2. Box plots of the simulation results of (a) mean annual *T* and (b) mean annual *P* and the bias correction results of (c) mean annual *T* and (d) mean annual *P* from 28 GCMs for the period 1971–2000 in the 14 river basins. The boxes denote the interquartile model spread (range between the 25th and 75th quantiles), with the horizontal line indicating the ensemble median and the whiskers showing the extreme range of the 28 CMIP5 model simulations. The blue dotted lines denote the observed results of mean annual *T* and mean annual *P* for the period 1971–2000. The basin number is consistent with that given in Figure 1.

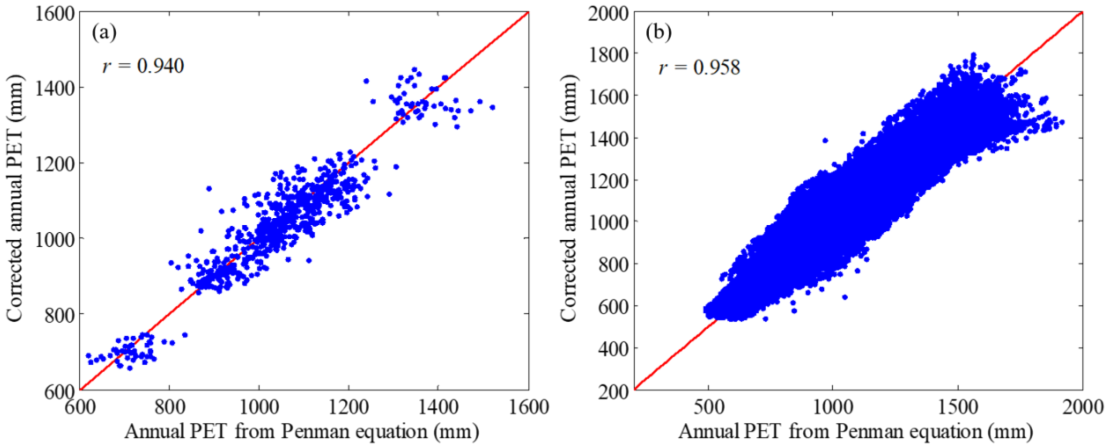

Figure 3. Comparison of annual *PET* calculated from the Penman method and the Thornthwaite method corrected by Equation (1) during the period 1960–2008 for (a) the 14 river basins and (b) all 0.5^{o} grid points over China.

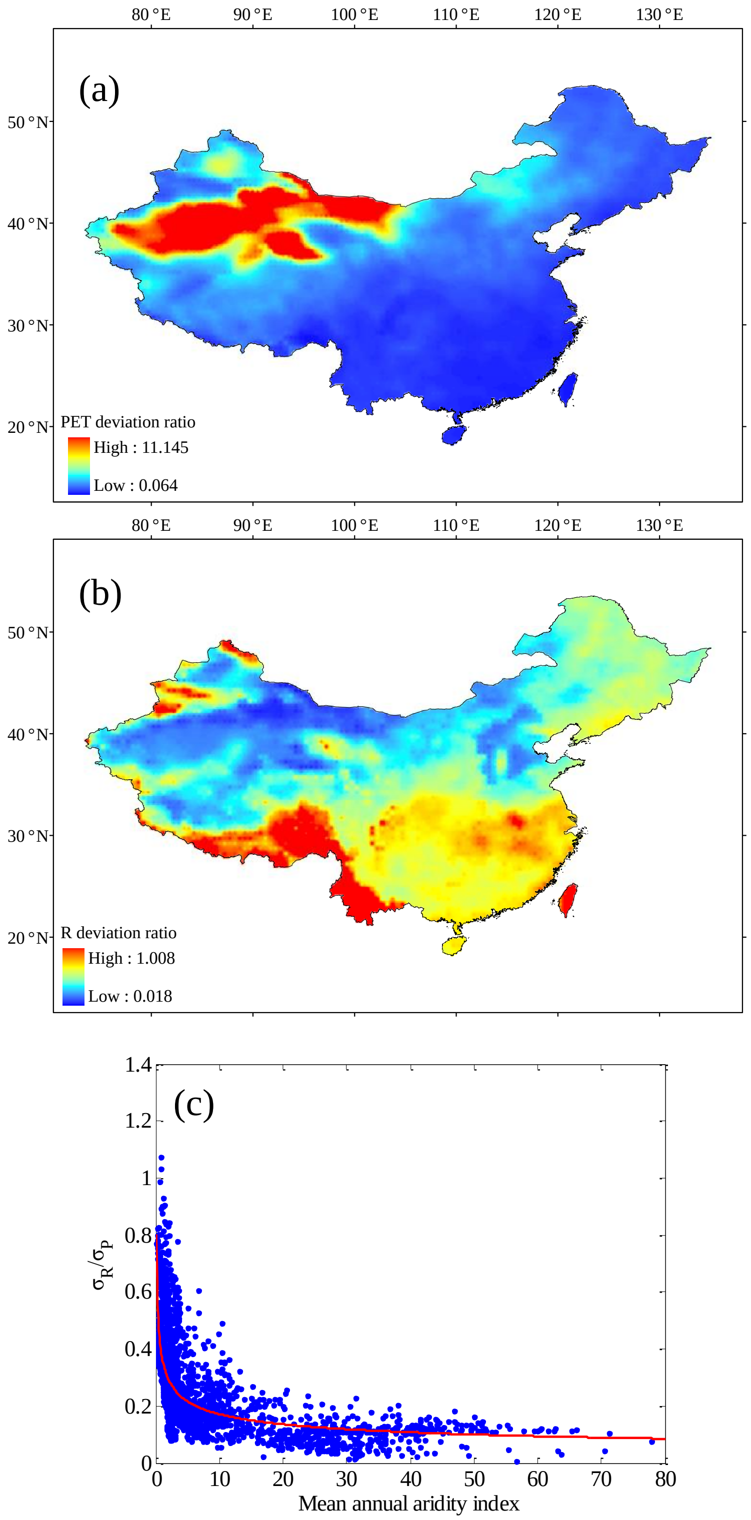

Figure 4. Spatial distributions of (a) *PET* deviation ratio and (b) *R* deviation ratio and (c) the relationship between *R* deviation ratio and mean annual aridity index ($\bar{\phi}$) for all 0.5^{o} grid points in China.

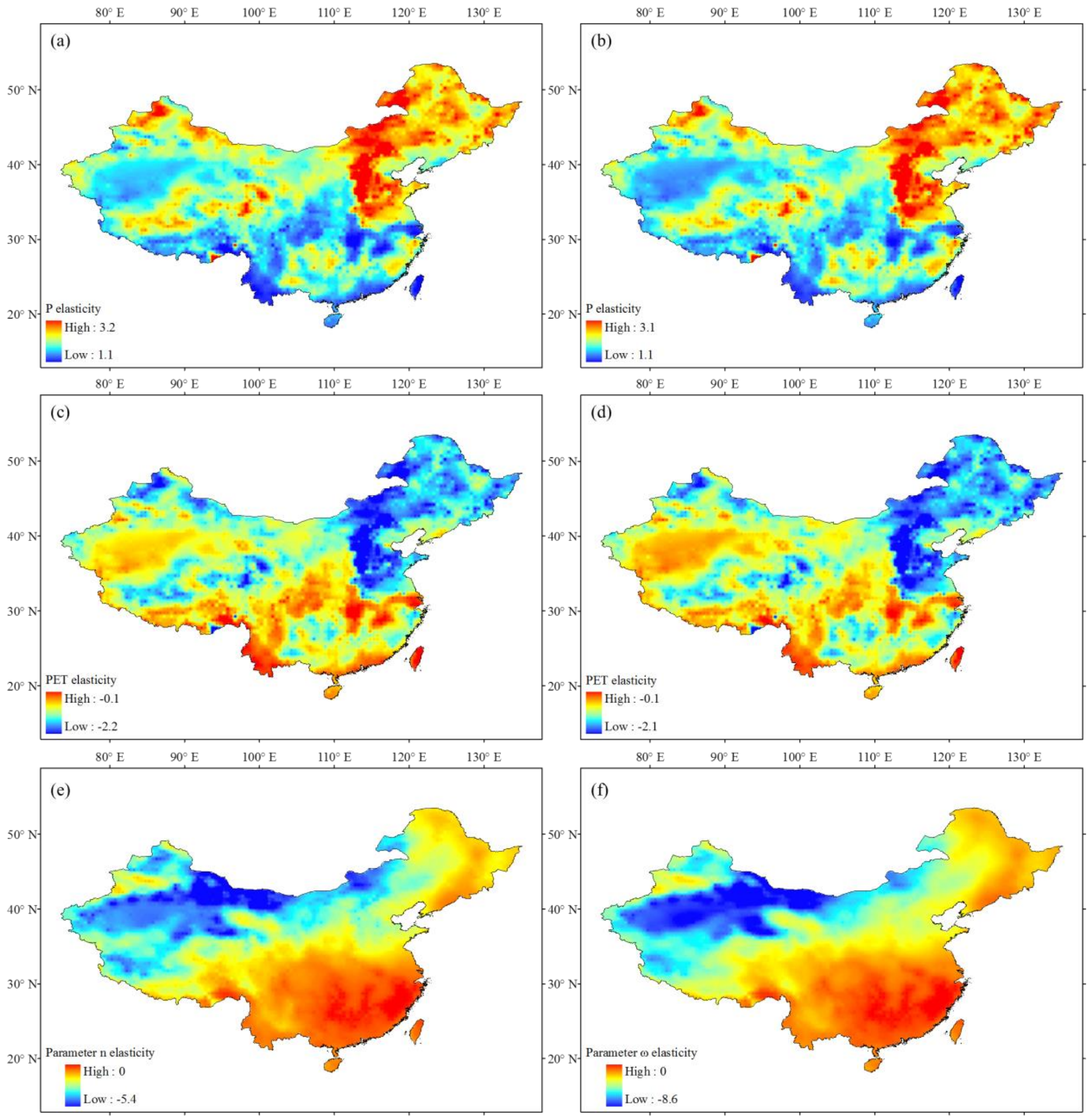

Figure 5. Spatial distributions of the *P* elasticity of *R* across China from (a) Equation (2) and (b) Equation (3). Spatial distributions of the *PET* elasticity of *R* across China from (c) Equation (2) and (d) Equation (3). Spatial distributions of the parameter elasticity of *R* across China from (e) Equation (2) and (f) Equation (3).

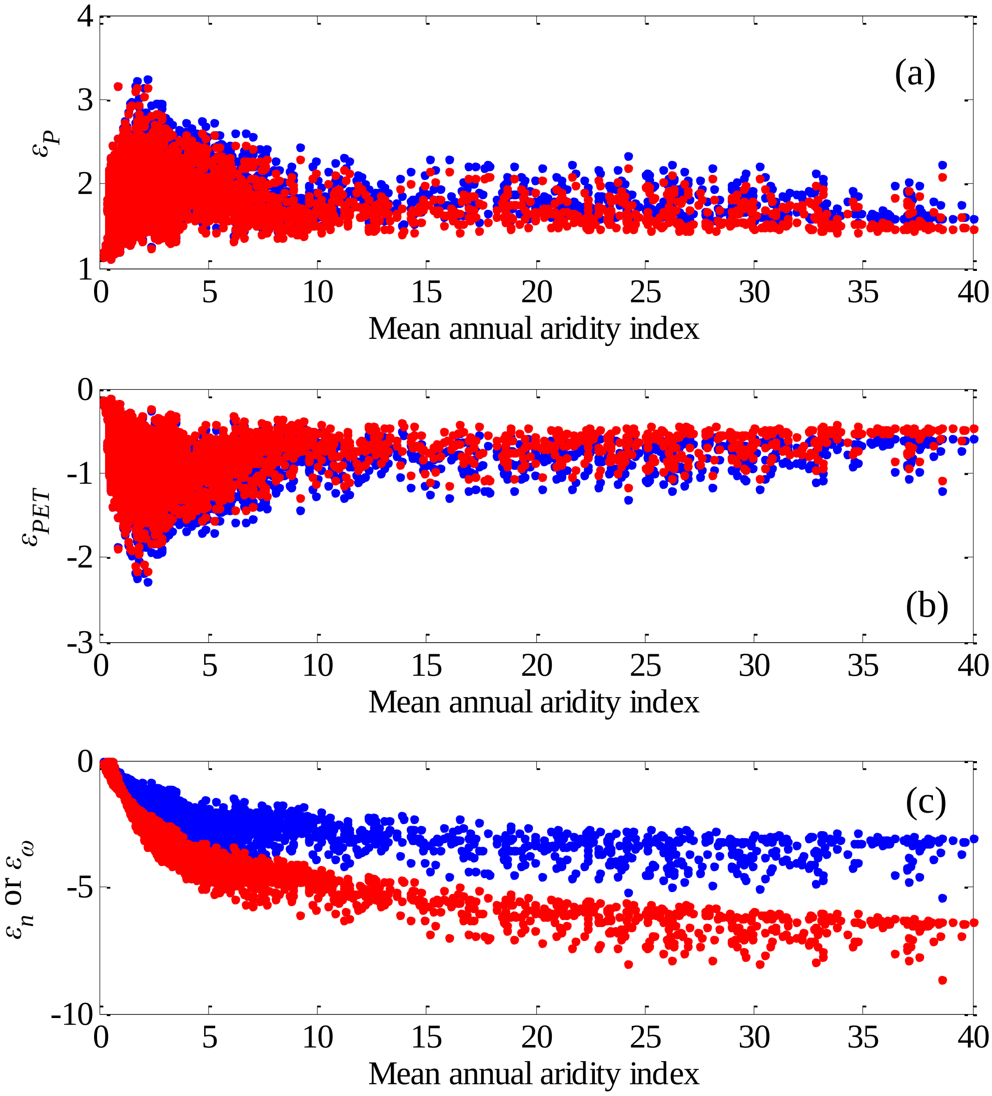

Figure 6. The relationship between mean annual aridity index and (a) *P* elasticity, (b) *PET* elasticity, and (c) parameter elasticity. The blue points represent the case of Equation (2), and the red points represent the case of Equation (3).

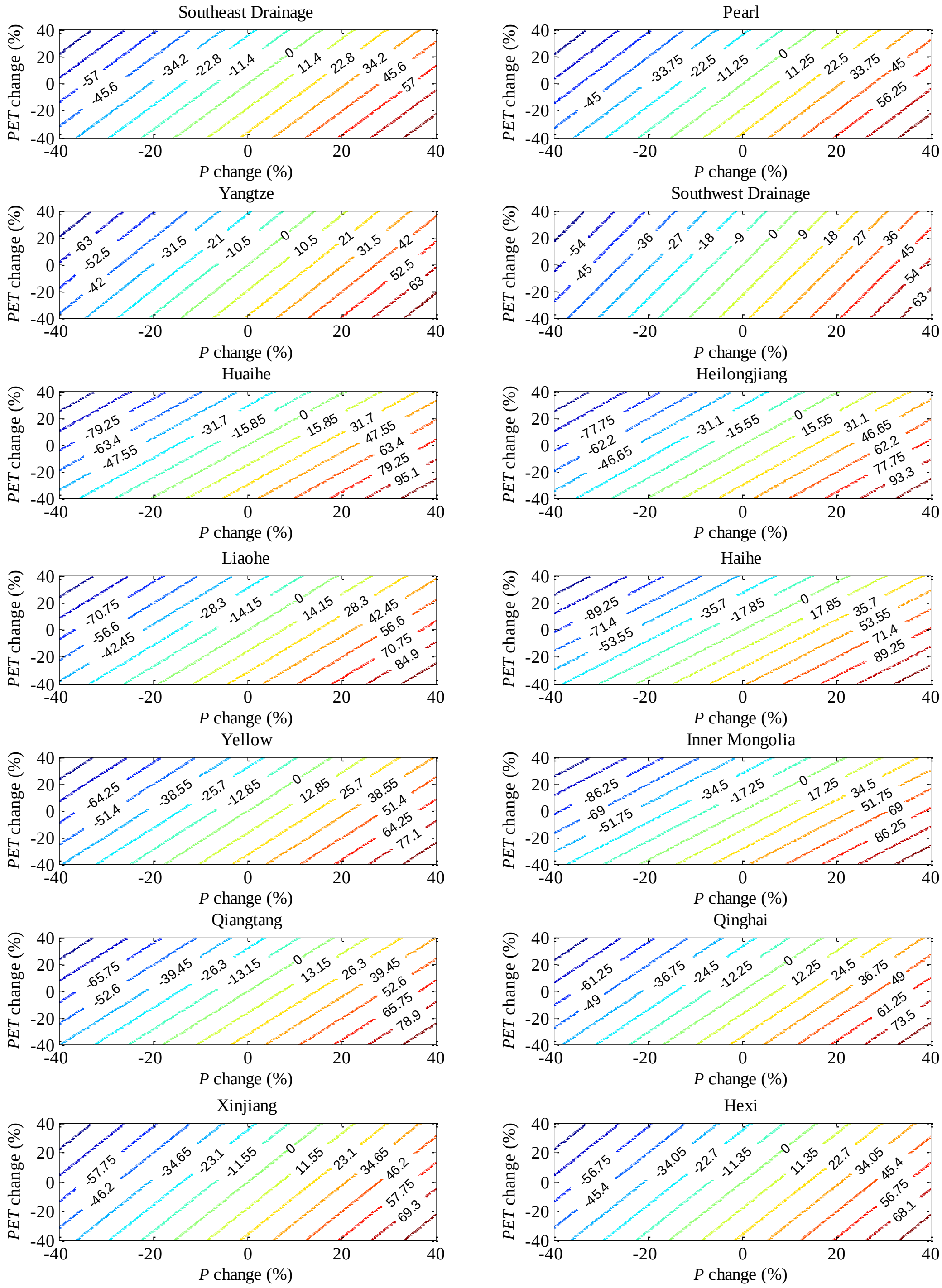

Figure 7. Contour plot of percentage *R* change due to the changes in *P* and *PET* for the 14 river basins. The *P* elasticity and *PET* elasticity of *R* are estimated based on Equation (2).

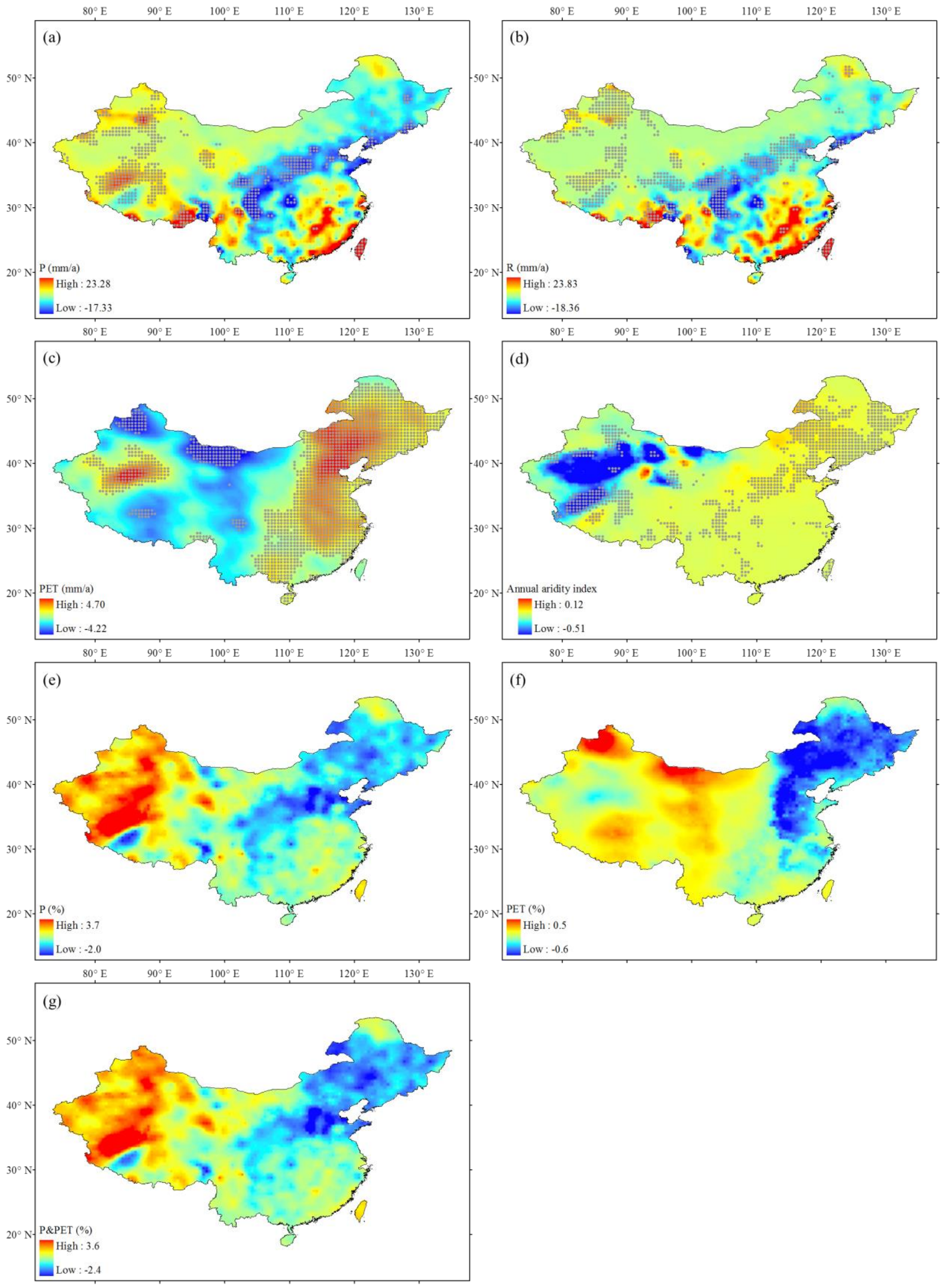

Figure 8. Trend magnitudes in annual time series of (a) *P*, (b) *R*, (c) *PET*, and (d) aridity index for the period 1960–2008 and spatial distributions of the contributions (unit: % yr^{-1}) of (e) *P*, (f) *PET*, and (g) climate (i.e. *P& PET*) to *R* in China for the period 1960–2008. The trend magnitudes are estimated by the Sen's method. Grey dots are shown as statistically significant positive/negative trends ($p < 0.05$).

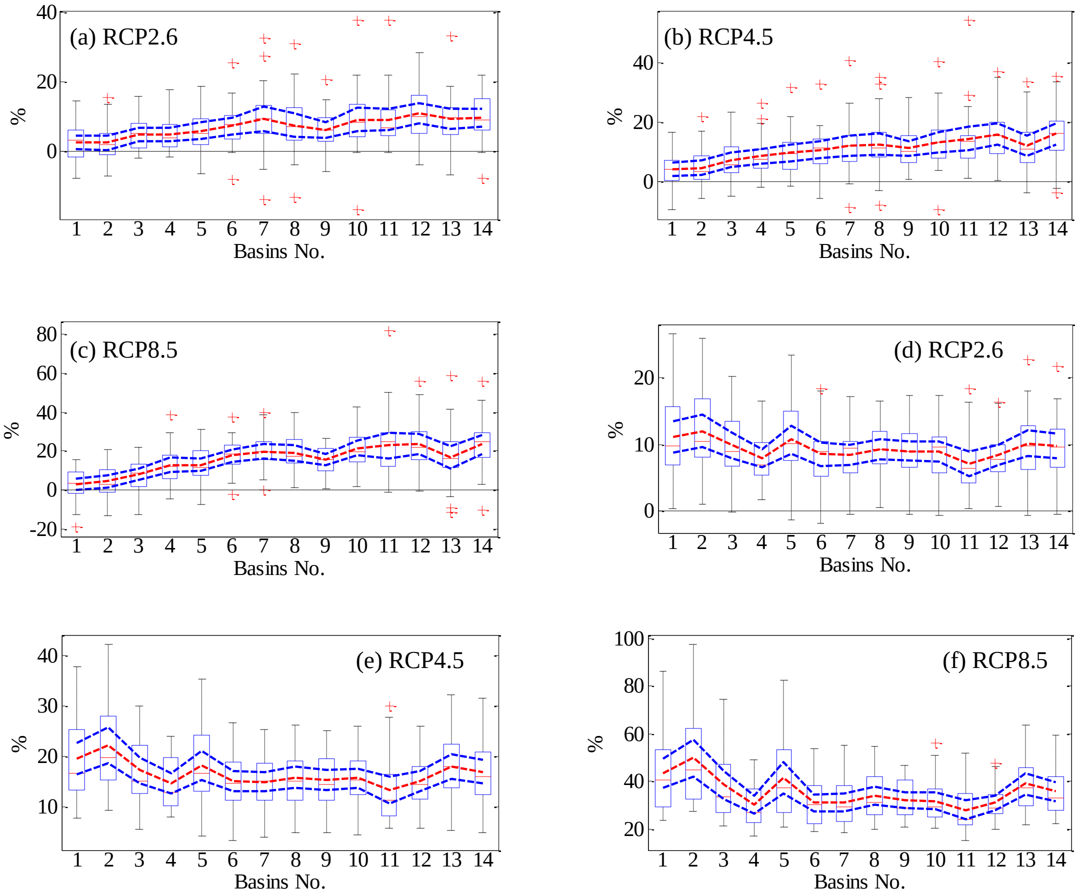

Figure 9. Box plots of relative change (%) in mean annual *P* under (a) RCP2.6, (b) RCP4.5, and (c) RCP8.5 scenarios and in mean annual *PET* under (d) RCP2.6, (e) RCP4.5, and (f) RCP8.5 scenarios calculated from 28 CMIP5 models in 14 basins for the period 2071–2100 (relative to the baseline 1971–2000). The boxes denote the interquartile model spread (range between the 25th and 75th quantiles), with the horizontal line indicating the ensemble median and the whiskers showing the extreme range of the 28 CMIP5 model simulations. Red dotted lines denote the average values of the multi-model ensemble. Blue dotted lines denote the 95 % significance levels range of the average values of the multi-model ensemble. The basin number is consistent with that given in Figure 1.

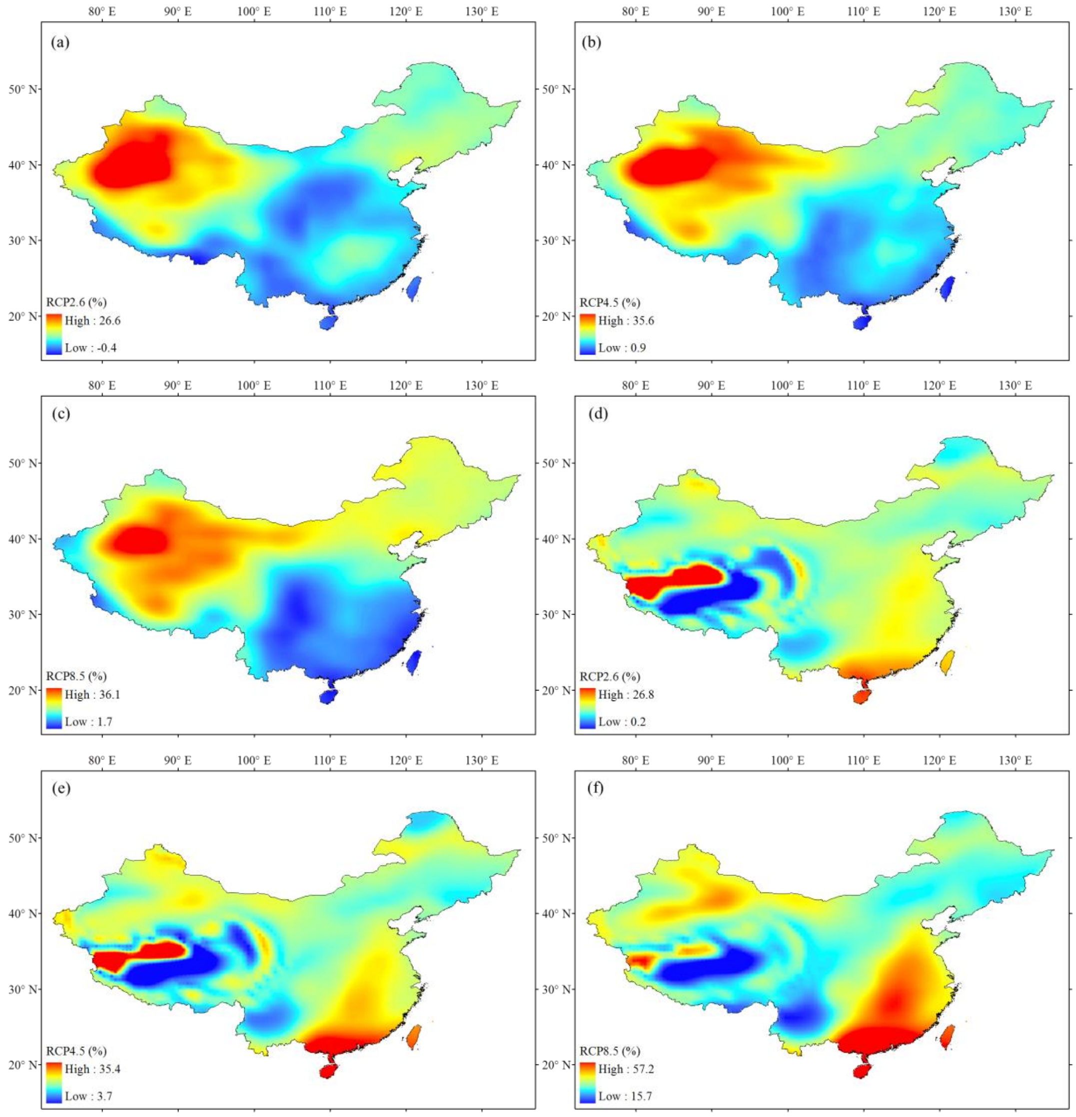

Figure 10. The CMIP5 multi-model ensemble median relative change (%) in mean annual *P* under (a) RCP2.6, (b) RCP4.5, and (c) RCP8.5 scenarios and in mean annual *PET* under (d) RCP2.6, (e) RCP4.5, and (f) RCP8.5 scenarios in China for the period 2071–2100 (relative to the baseline 1971–2000).

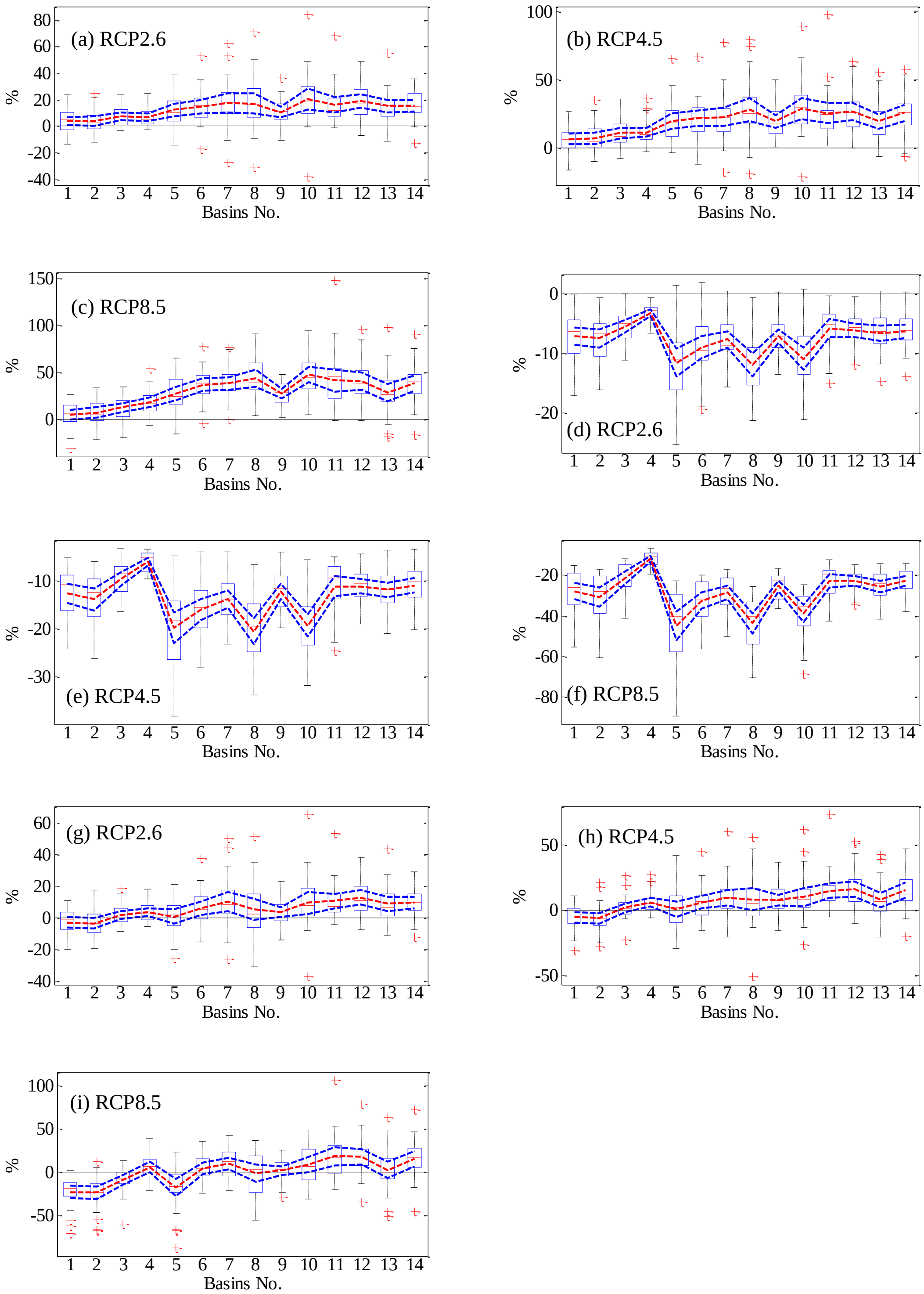

Figure 11. Box plots of relative change (%) in the contributions of annual *P* to *R* under (a) RCP2.6, (b) RCP4.5, and (c) RCP8.5 scenarios, in the contributions of annual *PET* to *R* under (d) RCP2.6, (e) RCP4.5, and (f) RCP8.5 scenarios, and in the contributions of climate to *R* under (g) RCP2.6, (h) RCP4.5, and (i) RCP8.5 scenarios calculated from 28 CMIP5 models in 14 basins for the period 2071–2100 (relative to the baseline 1971–2000). The boxes denote the interquartile model spread (range between the 25th and 75th quantiles) with the horizontal line indicating the ensemble median and the whiskers showing the extreme range of the 28 CMIP5 model simulations. Red dotted lines denote the

average values of the multi-model ensemble. Blue dotted lines denote the 95% significance levels range of the average values of the multi-model ensemble. The basin number is consistent with that given in Figure 1.

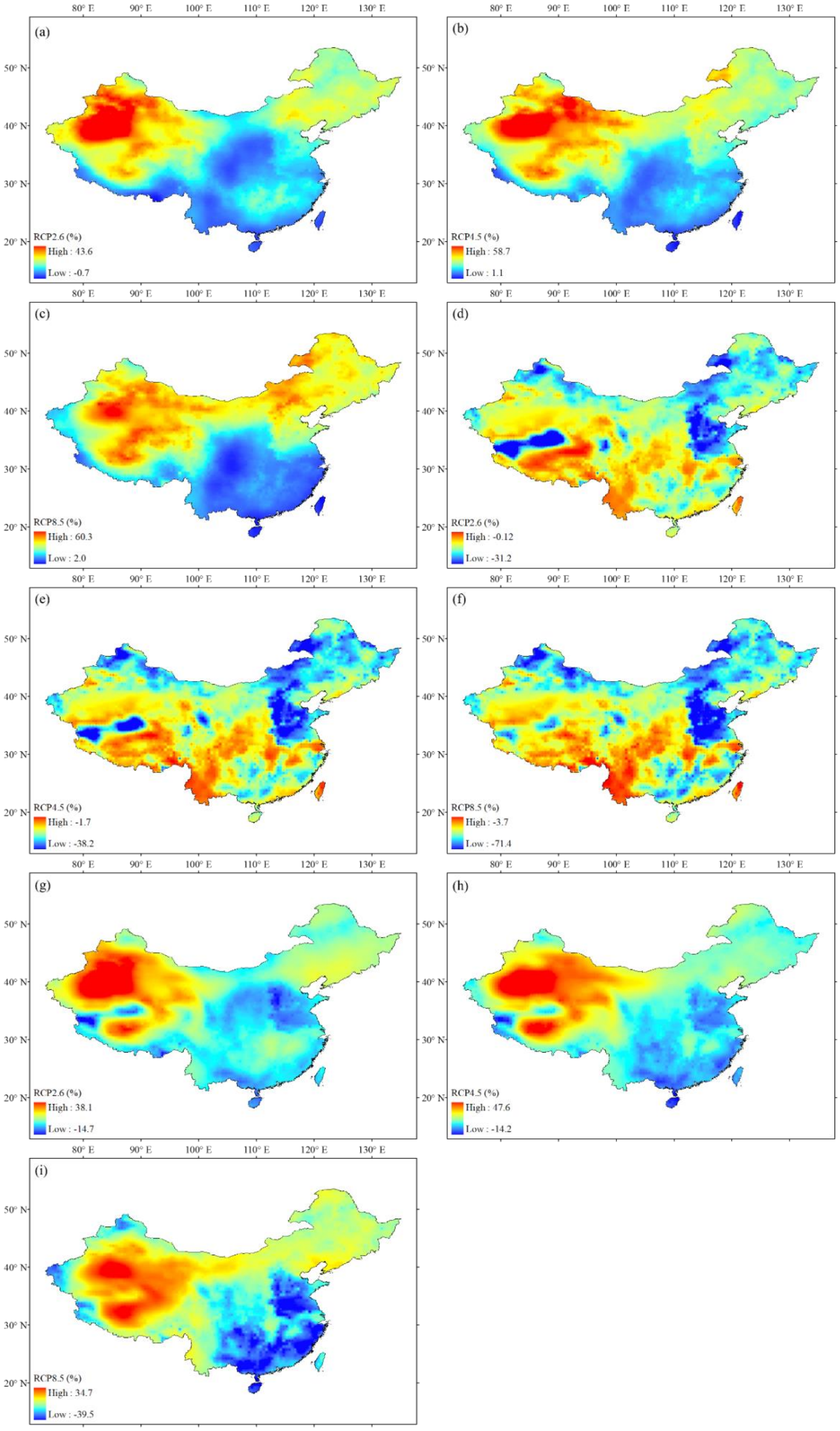

Figure 12. The CMIP5 multi-model ensemble median relative change (%) in the contributions of annual *P* to *R* under (a) RCP2.6, (b) RCP4.5, and (c) RCP8.5 scenarios, in the contributions of annual *PET* to *R* under (d) RCP2.6, (e) RCP4.5, and (f) RCP8.5 scenarios, and in the contributions of climate

to *R* under (g) RCP2.6, (h) RCP4.5, and (i) RCP8.5 scenarios in China for the period 2071–2100 (relative to the baseline 1971–2000).

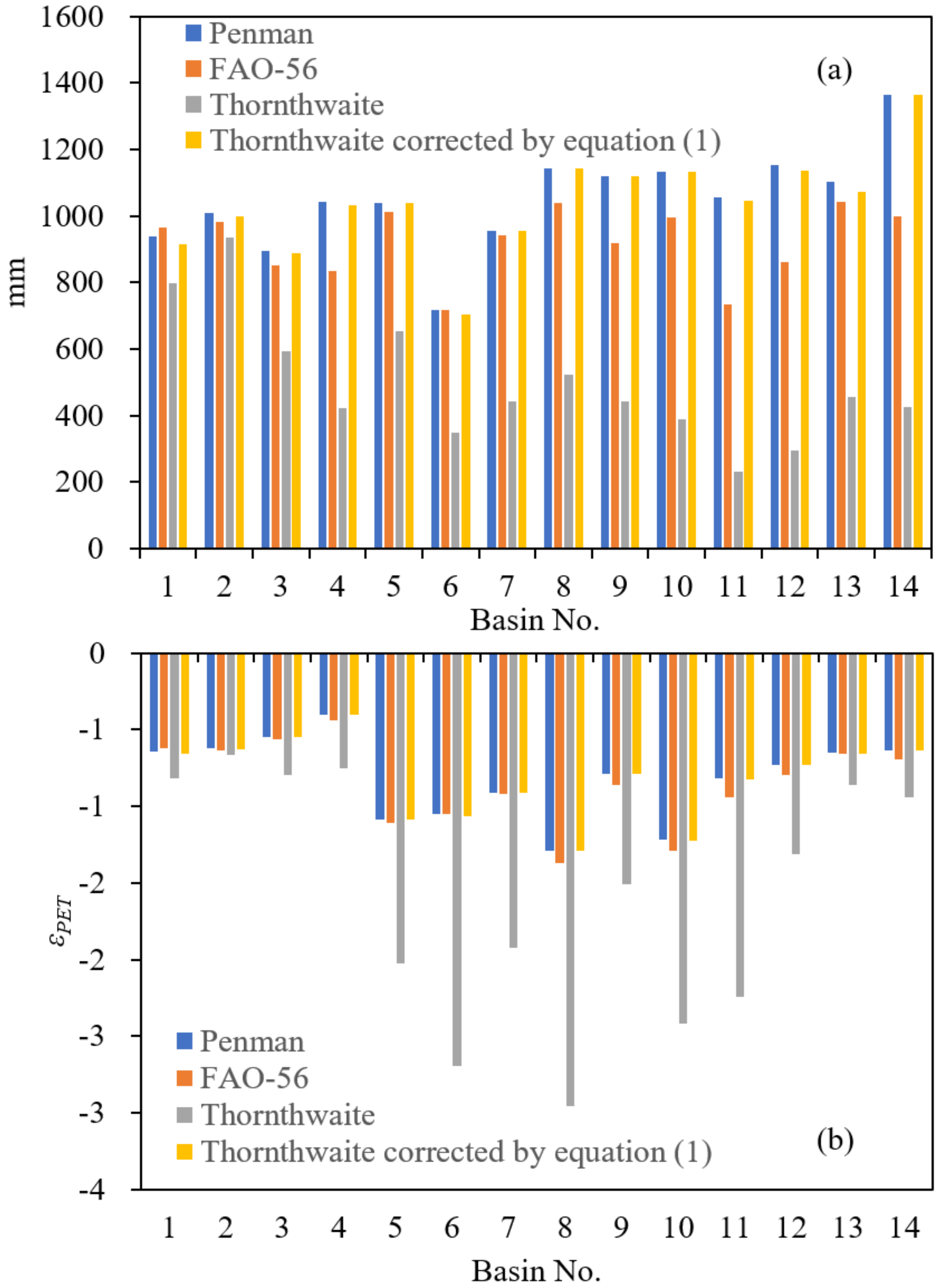

Figure 13. (a) Mean annual *PET* calculated from the four methods for the 14 river basins of China during the period 1960–2008. (b) *PET* elasticity calculated from Equation (2) based on the four *PET* data for the 14 river basins of China during the period 1960–2008. The basin number is consistent with that given in Figure 1.

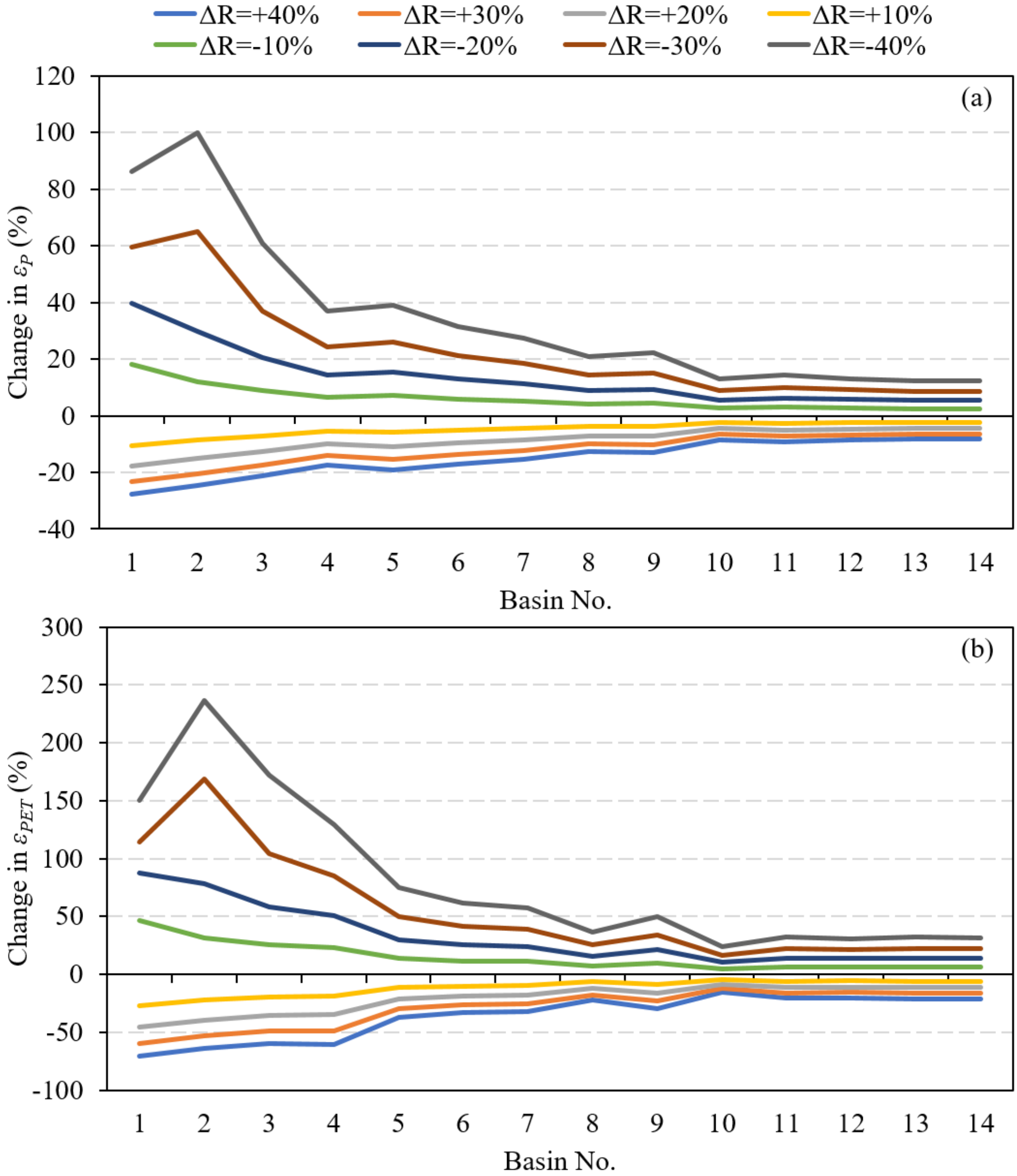

Figure 14. Comparison of changes in (a) *P* elasticity and (b) *PET* elasticity in response to changes in *R* for the 14 river basins of China. The basin number is consistent with that given in Figure 1.