## Author response to Referee #1 comments

Dear Prof. Michael Roderick,

Thank you for your pertinent comments and kind suggestions of our manuscript entitled "Historical and future trends in wetting and drying in 291 catchments across China" (hess-2015-588). Your previous work (Roderick et al 2014 HESS) does inspire us a lot, and we really treasure your comments on this study. Benefiting from your viewpoint to our study's scientific logic, we have revised it to be more acceptable.

The start point of this study originates from the Peter Greve's study (Greve et al., 2014), in which the DDWW pattern is so attractive that it implies a more uneven distribution of the water availability globally under the climate changes. Though the DDWW pattern doesn't hold according to Greve's study, we have an intuition that the pattern has a fair chance to hold in China. Based on semi centennial observed hydrologic and meteorological data of 291 catchments, we indeed find some results similar to the DDWW pattern. However, we present our findings from an unnatural point to modify the DDWW pattern proposed in Greve's study by adjusting the definition of dry and wet areas based on a threshold in the aridity index. It misleads readers to thinking that the core idea of this study is that the selection of the threshold determines whether the pattern holds or not. In fact, any adjustment to the threshold traps itself in a dilemma where people can always find a different threshold in other regions. Finally, we realize that the uneven trend of the water availability should not be summarized by the DDWW pattern based on a specific threshold, but a statement considering the uncertainty of the threshold. Such statement can be like "drier regions are more likely to become drier, and wetter regions are more likely to become wetter", which may be a universal conclusion around the world, and it is the most significant change in the logic of our study. In our revision, we will present how the revised pattern works in China.

Based on this new logic, we focus on illuminating the fact that the distribution of water resources (runoff) has become more uneven in China since 1950s. In Greve's study, the aridity index is recommended as an indicator of the water availability within a grid for that runoff isn't acquirable in the modelled data. However, since we have the observed streamflow data, the mean annual runoff  $(\bar{Q})$  is a more direct and appropriate choice of reflecting a catchment's water resource condition in this study, which has been neglected in our previous study. The simple framework based on the Budyko hypothesis will still be adopted to model the runoff trend based on the meteorological data in the same period as the observed hydrologic data, revealing the historical runoff change is a response to the change in precipitation basically, as Roderick et al 2014 HESS stated. So the cause of the more uneven trend can be summarized that "*more precipitation in wetter areas, and less in drier areas*". Furthermore, we concerned about whether the water resources in China will continue to be more uneven in the future, and the simple model provides us an acceptable way to predict future trends based on CMIP5 projected data.

We appreciate your advice to re-evaluate our underlying logic of the study. We will add the contents that you suggested to assess the CMIP5 model projections, checking whether precipitation is still the most significant factor in the future (Section 3.3 in the revised manuscript). As for the CMIP5 simulations, since we have already acquired the observed data, we think that it is better to

use the observed in the process of finding the key factor. And at the same time, the simulations will still be adopted to compare with the observed data in the revised version.

You pointed out that there is non-climate related changes in the runoff in the actual catchments, and asked us for an approach to exact them. In our study, to eliminate the effects of non-climate factors as much as possible, we prudently select the restored streamflow data of catchments that are far away from human activities. Although the effects cannot be removed totally due to the lack of information and technical defects, the restored data are closest to the real natural condition taking all available data into account. We might as well consider it as the real natural runoff (very close), and we can calculate the real natural runoff trend. As for the Budyko-estimated trend, it can be seen as the estimated climate-caused runoff trend, which is the estimated part of the runoff trend directly related to the climate changes. So the residual error between them can be considered as the trend induced by other natural factors, such as land use and vegetation. This also has been elucidated in the third paragraph of Section 1.

Our detailed replies to your comments are listed as follows, and we hope that they are satisfying. Please note that the listed pages and lines correspond to the marked-up manuscript version attached in the end of the responses.

**Comment 1**: P2, line 10. Why the Greve reference? The original DDWW was Held and Soden 2006? **Reply to Comment 1**:

We are sorry for our carelessness in the paper references and some impertinent summaries of them. We removed the Greve reference in P3L3 in the revision, and avoided to say "first proposed" to make "original" confusing. Actually when we say "original", we refer to the DDWW pattern proposed by Held and Soden (2006) rather than the pattern proposed in this study.

**Comment 2**: P 2, line 14, Why the Lim and Greve references? The point about the ocean dominance was originally made by Roderick et al 2014 HESS and was relevant to model projections and not observations.

## **Reply to Comment 2:**

Thank you for your reminding. We revised this content in P3L17-20 in the revision.

**Comment 3**: P. 2, line 18. Why the Roderick reference? That paper did use the phrase salt get saltier, etc.., but the underlying results were from a paper by Durack? Perhaps say something like ...... Oceanic observations (Durack et al 2012) confirm a fresh get fresher and salty get saltier pattern (as reinterpreted by Roderick et al 2014 HESS).

#### **Reply to Comment 3:**

We added the Durack et al (2012) reference in the revision and can be seen in P2L31.

**Comment 4**: P. 2, lines 17-18. Another generalisation relevant here is that rainfall has increased in places with low rainfall and decreased in places with high rainfall (Sun et al 2012 GRL; Donat at al 2016 Nature Climate Change).

## **Reply to Comment 4:**

Thank you for your suggestion, and we indeed showed more relevant generalizations in our revised

manuscript and are shown in P2L24-31.

**Comment 5**: P. 4, line 6. You use Penman for PET. The earlier work by Roderick et al 2014 HESS actually followed Budyko and used net irradiance (and not Penman PET). Using Penman PET is not appropriate for vegetated surfaces when CO2 is changing (e.g. Roderick et al 2015 WRR, Milly and Dunne 2016 Nature Climate Change). For that reason you really need to consider using net radiation. It would be of interest to contrast the net radiation based results with those when the Penman PET is used.

#### **Reply to Comment 5:**

Thanks for your suggestion, which gives us inspiration for understanding the role of radiation in catchment hydrology, and we will focus on it in the future researches. In this study, considering large regional variation in climatic variables (such as humidity, temperature, and wind speed) in China, we chose Penman equation for estimating PET because it includes effects from humidity and wind speed on PET. We think that Penman equation might have a large ability in capturing regional variation of atmospheric evaporative demand across China, and the equation has been adopted by previous researches like Yang et al., (2014) and Kai Xu et al., (2015). Additionally, the other referee seems to accept the use of Penman equation, and we added **Appendix A** in our revision to further elucidate the process of computing Penman potential evaporation as he suggested.

Comment 6: Eqn 3. Why c? Later you use n (e.g. Eqn 4).

**Reply to Comment 6:** We use c to represent the general parameter that measures the catchment property, while n can be considered a special c in Yang's Equation, as in Fu's Equation it becomes  $\omega$ .

**Comment 7**: Eqn 7. Niether Arora 2002 or Fu et al used that form of the three-term partial differential equation. Why are they cited?

#### **Reply to Comment 7:**

We removed these two references in the revision and can be seen in P8L15.

**Comment 8**: P. 6 line 26. Units. Here and elsewhere. The units of Q are mm a-1. The trend in Q has units mm a-2. The units of Annual Q are mm. The key here is that the prefix Annual denotes an integration. The trend in Annual Q has units mm a-1. So to use those units (mm a-1) for the trend you better put Annual in front of Streamflow at the start of the sentence. Same comment applies throughout.

## **Reply to Comment 8:**

It is so nice of you to point out our carelessness in this study again. Actually we hadn't thought over the choice of units until Prof. Roderick warned in the comment. We indeed confused some concepts and thus their units. We corrected the use of units according to your suggestion in the revision.

**Comment 9**: p. 7, line 6. The sentence starting "However, in both situations ...." does not make sense?

**Comment 14**: P. 11, lines 20-23. This relates to the last comment in the main comments. On page 3, lines 1-2 you correctly point out the need to account for land-use and/or land cover changes. But you did not attempt that. This might be an English problem? Earlier (page 3, line 2) you need to say it is important but here we will ignore it – because that is what you did. Then at the end you need to

say - we should not have ignored it (p. 11, lines 20-23). This whole part of the manuscript needs to be explained more clearly.

## **Reply to Comments 9 and 14:**

We have carefully modified the manuscript to make any sentences meaningful and our purpose more clear to be caught, trying to avoid English expression problems in our revision.

**Comment 10**: P. 7, lines 7-11. What is the logic of this? See main comments at the beginning. **Reply to Comment 10**:

We have adjusted our logic of the study, and the details are shown above.

**Comment 11**: P. 9, Section 4.2. Why introduce new RESULTS in the DISCUSSION. I did not see the value of this entire section. However, if you want to keep it, then it needs to be moved back to RESULTS.

**Comment 12**: P. 10, Section 4.3. Same again. You cannot introduce new RESULTS in the DISCUSSION. If you want to keep it, then move it back to the RESULTS.

## **Reply to Comments 11 and 12:**

Thanks a lot! Following your comments, we rearranged our sections in the revision by merging **Results** and **Discussion** together into a section **Results and Discussion** to avoid this problem.

**Comment 13**: Fig. 12. Left Panel. This is truly astonishing. That is the best fit between modelled and observed rainfall I have ever seen! Are you sure of the analysis? I ask because the last sentence of the paper (p. 12, lines 1-2) says that the modelled rainfall was poor? But the results in the left panel of Fig. 12 are truly astonishing. Perhaps I have missed something?

## **Reply to Comment 13:**

Thanks for pointing out this issue! After inquiring the data provider from the Institute of Environment and Sustainable Development in Agriculture, the Chinese Academy of Agricultural Sciences, China, we found out the reason why the simulated and observed *P* fit well, and it should be owning to the bias-correction process. All GCM outputs (precipitation; mean, maximum and minimum air temperature; solar radiation; wind speed; and relative humidity) were bias-corrected according to observations, but we don't know exactly based on which data the process has been implemented. The results in Section 3.3 implies the great effectiveness of the correction to P but the failure in outputs related to Ep. Moreover, we realized it is the last sentence of the paper that led to this misapprehension, in which we actually meant to emphasize the uncertainty of GCMs and the deviation between simulated and observed Ep should be blamed instead. Therefore, in our revision, we have deleted the saying that "the modelled rainfall was poor", and focused on the badly simulated Ep.

## Reference

Xu K, Yang D, Yang H, et al. Spatio-temporal variation of drought in China during 1961–2012: A climatic perspective[J]. Journal of Hydrology, 2015, 526: 253-264.

Yang H, Qi J, Xu X, et al. The regional variation in climate elasticity and climate contribution to runoff across China[J]. Journal of Hydrology, 2014, 517: 607-616.

## Author response to Referee #2 comments

We thank you for your patient attention on our manuscript entitled "Historical and future trends in wetting and drying in 291 catchments across China" (hess-2015-588) and valuable feedbacks. Your valuable comments and remarks really inspire us to improve our study and revise our article. Following your comments and remarks, we have finished the revised version of our manuscript. Please note that the listed pages and lines correspond to the marked-up manuscript version attached in the end of the responses. Detailed responses to your comments are listed below:

**Comment 1**: Runoff trends may have been caused by human alterations, water abstractions and land cover changes. Many papers have already shown the relevance of this for runoff trends in China. How were catchments selected to the keep this influence low? What would be the effect on the interpretation of the results?

## **Reply to Comment 1:**

To keep this influence low, we adopted the "restored" discharge data in our research, meaning the effects of the human activities to the runoff generation within catchments are mostly removed via some technical means by the Hydrological Bureau of the Ministry of Water Resources of China. Of course the effects cannot be completely removed, but we take it as the most credible data set we have got to describe the natural discharge. The detailed elucidation of this issue is revised in Paragraph 3 in Introduction in the revision.

**Comment 2**: Discuss patterns of historical precipitation changes in China, do these trends in P follow the DDWW pattern?

## **Reply to Comment 2:**

This is an inspiring advice, and we added relevant contents to our revision in Section 3.2 in P12L17-20. By relating trends in P with mean annual runoff  $\overline{Q}$ , we find a similar pattern as the new DDWW pattern we proposed in our revision that "more precipitation are more likely in wetter areas, and vice versa", which interprets the DDWW pattern from the perspective of the climate change that the more uneven precipitation results in more uneven runoff.

**Comment 3**: I believe that the existence of a DDWW pattern has many implications also for water resources. A brief discussion of the implications would emphasize the relevance of the findings! **Reply to Comment 3**:

We agree with you! In fact, we were meant to reflect the more uneven distribution of the water resources by the existence of the DDWW pattern, but we didn't express it well in the original manuscript. Therefore, in our revision, we tried elucidating the DDWW pattern in the aspect of the water resources. In Section 3.1, after proposing our new DDWW pattern that "drier regions are more likely to become drier, whereas wetter regions are more likely to become wetter", we interpreted it as a signal of the more uneven trends in the distribution of the water resources in China since 1950s.

#### **Comment 4**: add which significance test was used in methods.

## **Reply to Comment 4:**

Following your suggestion, we used the t-test, and we added this contents in P6L23 in the revision.

**Comment 5**: add details for computation of Penman potential evaporation (observations and GCM) in methods or appendix.

## **Reply to Comment 5:**

Following your suggestion, we gave a detailed description of the computation of Penman potential evaporation using GCM outputs in Appendix A in the revision, and that about the observed PET data are offered by Yang et al., (2014).

**Comment 6**: please explain better Fig 11 such that the reader can understand the conclusions in section 4.2.

**Comment 7**: Fig. 11 maybe add the Budyko curve with n = 1.8 to the plots.

## **Reply to Comments 6 and 7:**

We highly appreciate your suggestions. We deleted this part of contents in our revision for the obscurity of them and focused on elucidating P is the most key factor in the climate change.

**Comment 8**: discuss the role of bias correction / spatial resolution of GCM output - when looking at Fig 12 it seems that P was corrected but not all variables needed to calculate E0

## **Reply to Comment 8**:

This is a meaningful suggestion to our study because we didn't realize that it might be the role of bias-correction that led to different simulated results in P and Ep until you referred to. After inquiring the data provider from the Institute of Environment and Sustainable Development in Agriculture, the Chinese Academy of Agricultural Sciences, China, we assured that the bias-correction process had been implemented to all GCM outputs (precipitation; mean, maximum and minimum air temperature; solar radiation; wind speed; and relative humidity), meaning all variables needed to calculate Ep were corrected simultaneously. Then why did there still exist so huge discrepancy between the simulated and observed Ep? We speculated that it might be related to the disparate effectiveness of the bias-correction process in different outputs, resulting in good fit to P and bad fit to Ep.

## Comment 9: do GCMs reproduce the runoff trends / patterns?

**Comment 10**: I checked some GCM projections for precipitation changes in China (Roderick et al., 2014, Hagemann 2013 ESD, IPCC AR5) and the projected precipitation changes are indeed different from the runoff trends shown in Fig. 8. Thus it seems that the GCM simulated precip changes in China are different from the historical ones observed in China.

## **Reply to Comment 9 and 10:**

Comment 9 raised a good question that we were also concentrated on. However, we are sorry to say that based on the data we've got now, we cannot drive a convincing result in historical period using the GCM data. In Section 3.3 in the revision, we revealed the great discrepancy between the observed and simulated Ep, and since this study didn't get the simulated E data, we could only estimate the historical runoff trends using simulated P and Ep based on the framework. Hence, the estimated runoff trends are believed to have great uncertainties as the projections and a great discrepancy is expected. Now that we have already got observed P and Ep data to verify the DDWW pattern, there's no need to examine the pattern in a dubious situation.

## Minor comments:

abstract: P1L12: be more precise than "simulated data"

P1L25ff rephrase

P3L14: what is meant with restored streamflow data?

P5L15: for which period was n determined?

P8L3: it is somewhat unclear for which variable and period the coefficient of variation

Cv was actually determined? Please specify.

**Author response to minor comments**: Thank you for your pertinent comments! We have seriously modified our article according to these 5 comments. We explained the "restored streamflow data" in P5L15-17. The period for which n was determined is 1956-2000 and can be found in P8L8. We talked more about Cv in P9L23-28.

# Historical and future trends in wetting and drying in 291 catchments across China

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#### 10 Abstract

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An increasingly uneven distribution of hydro-meteorological factors related to climate change has been detected by global climate models (GCMs), and the pattern of changes in water availability is commonly described with the phrase "*dry gets drier, wet gets wetter*" (DDWW). However, the DDWW pattern is primarily dominated by oceanic areas, and recent studies based on both observed and modelled data have failed to verify the DDWW pattern on land. The "*dry gets drier, wet g* 

- 15 wetter" (DDWW) pattern is a popular catchphrase to summarize hydrologic changes under global warming. However, recent studies based on simulated data have failed to obtain a feasible DDWW pattern for runoff trends. This study tested confirms the existence of a new\_DDWW pattern using observed streamflow and meteorological data from 291 catchments in China after analysing the observed streamflow data from 291 Chinese catchments from 1956 to 2000, revealing that the distribution of water resources has become increasingly uneven since 1950s. This pattern can be more accurately described as "drier
- 20 regions are more likely to become drier, whereas wetter regions are more likely to become wetter", interpreted it using a simple method derived from the Budyko hypothesis, and explored its future evolution according to the projections of five global climate models (GCMs) from the Coupled Model Intercomparison Project Phase 5 (CMIP5). Similar to the DDWW pattern, the results show that catchments with an aridity index of  $\varphi < 1$  become wetter and that catchments with  $\varphi > 1$  become drier, with nearly 80% of the studied catchments following this pattern. However, the pattern does not hold in
- 25 glacier regions due to the effects of melting ice and snow. Based on a framework derived from the Budyko hypothesis, this study estimates runoff trends via observations of precipitation (*P*) and potential evapotranspiration ( $E_p$ ) for the same period, finding that a high correlation exists between the estimated and observed runoff trends ( $R^2$ =0.70) and that the DDWW pattern also appropriately describes the estimated trends, precipitation and potential evapotranspiration changes, the firstorder differential of the Budyko hypothesis can provide a good estimate of runoff changes ( $R^2$ =0.70). Therefore, climate
- 30 change has led to the historical trends in runoff as well as the DDWW pattern, with changes in *P* playing the most significant role, the atmospheric forcing of water and energy is the key factor in interpreting the DDWW pattern. Over 80% of the estimated trends have signs coincident with those of the measured trends, implying that the DDWW pattern can be assessed

with estimated data. Precipitation is the controlling factor that leads to the DDWW pattern in nearly 90% of catchments where observed and estimated signs are consistent. In the three tested scenarios (RCP2.6, RCP4.5 and RCP8.5), the different models produce significantly different predicted changes, even under the same scenario, whereas a given model yields similar results under different scenarios. Based on the projected results, the DDWW pattern no longer provides a reliable

- 5 prediction. However, this conclusion remains tentative due to the large uncertainty of the simulations. The considerable differences between the observed and modelled meteorological data for the same period suggest that this conclusion should be adopted with caution. Furthermore, the *P* and *E*<sub>p</sub> projections of five GCMs from the Coupled Model Intercomparison Project Phase 5 (CMIP5) under three scenarios (RCP2.6, RCP4.5 and RCP8.5) are used to predict the future trends in the study catchments from 2001 to 2050 based on the framework. Despite the differences among the predicted results of the
- 10 different models, the DDWW pattern does not hold in the projections, regardless of the model used. Unfortunately, most areas of China (over 60%) will experience water resource shortages under the projected climate changes. Nevertheless, this conclusion remains tentative due to the large uncertainties in the GCM outputs.

#### **1** Introduction

Terrestrial water availability is critical to human lives and economic activities (Milly et al., 2005). In recent decades, changes

- 15 in water availability have had significant effects on human society (Piao et al., 2010) and the environment (Arnell, 1999) in the context of climate changes. Runoff (*Q*) is a commonly adopted indicator of water availability (Milly et al., 2005). Both streamflow observations (e.g., Pasquini and Depetris, 2007; Dai et al., 2009; Stahl et al., 2010) and hydrological simulations (e.g., Hamlet et al., 2007; Alkama et al., 2013; Greve et al., 2014) have been used to investigate trends in *Q* in response to climate changes. The corresponding study areas range from the scale of individual river basins to the global scale. However,
- 20 significant spatial heterogeneity has arisen among different studies (Kumar et al., 2016). The response of Q to climate change has been widely investigated from the basin scale to the global scale, based on streamflow observations (e.g., Pasquini and Depetris, 2007; Dai et al., 2009; Stahl et al., 2010) or model outputs (e.g., Hamlet et al., 2007; Alkama et al., 2013; Greve et al., 2014).

Under the influence of climate change, a more uneven distribution of the hydro-meteorological elements has been detected

- 25 at the global scale by the global climate models (GCMs) both spatially (Held and Soden, 2006; Chou et al., 2009) and temporally (Chou et al., 2013) as well as the observed data (Allan, 2010; Durack, 2012; Liu, 2013), resulting in probable enhancement of hydrological extremes such as floods and droughts. This response is known as the "rich-get-richer" mechanism (Chou and Neelin, 2004), from which follow-up studies derive diverse summaries of different elements, such as"*dry gets drier, wet gets wetter*" for precipitation (*P*) (Allan, 2010) and precipitation minus evapotranspiration (P - E)
- 30 (Held and Soden, 2006), "*wet season gets wetter, dry season gets drier*" for seasonal precipitation (Chou et al., 2013) and "*fresh gets fresher, salty gets saltier*" for ocean salinity (Durack, 2012; Roderick et al., 2014). Furthermore, it attracts a lot of attention to explore whether there exists a similar effect in *Q* on land as the "*dry gets drier, wet gets wetter*" (DDWW

<u>hereinafter for short</u>) pattern found in P - E, which indicates the increasingly uneven distribution of the water resources. To elucidate spatial variations in runoff changes, the well known "*dry gets drier, wet gets wetter*" (DDWW) pattern (Greve and Seneviratne, 2015) can be taken into account. First proposed by Held and Soden (2006), tThe original DDWW pattern suggested predicted a simple active proportional relationship between P - E (precipitation – evapotranspiration) and  $\Delta(P -$ 

- 5 E) the projected changes in P E due to global warming. The as the sign of P E determines whether a region is dry (negative) or wet (positive). Two special points should be highlighted here regarding the results: one is that the results were mostly based on ocean data (Lim and Roderick, 2009; Greve et al., 2014), and the other is that the projected changes were averages of latitudinal zones rather than values at the local scale (e.g., grid box or catchment) (Roderick et al., 2014). Since then, conclusions analogous to the DDWW pattern have been reached in other studies, such as "wet season gets wetter, dry
- 10 season gets drier" for global precipitation (Chou et al., 2013) and "fresh gets fresher, salty gets saltier" for ocean salinity (Roderick et al., 2014). The generalized DDWW pattern can thus be seen as a series of qualitative descriptions of trends in hydrologic elements. Consequently, the widespread DDWW pattern leads to thinking whether such a pattern actually exists in runoff changes. The intimate relationship between Q and P - E (in the long term average, Q is equal to P - E over land) inspired an analogy of Held and Soden (2006). If the pattern of P - E works well over land, it can be reasonably extended to
- 15 Q. However, work performed by Roderick et al. (2014) rejected the original DDWW pattern over land at both the zonal and grid scales. Since the long term average P E is overwhelmingly positive on land, it is not appropriate to identify the aridity degree in this circumstance, as  $\Delta(P E)$  can obviously be negative. It should be noticed that the predicted changes were averages of latitudinal zones rather than values at the local scale (e.g., grid box or catchment), resulting in the dominance of the oceanic components in the DDWW pattern (Roderick et al., 2014), as P and E are dominated by exchanges over the
- 20 <u>ocean at most latitudes (Lim and Roderick, 2009). Thus, the DDWW pattern is more appropriately applied to the ocean than</u> to the land. In fact, because the long-term mean P - E is overwhelmingly positive on land, the method of using the sign of P - E to identify wet and dry regions is not feasible anymore, as  $\Delta(P - E)$  can obviously be negative. Therefore, some scholars tried to explore a new DDWW pattern to describe changes in the hydrological cycle on land at the local scale. Greve et al. (2014) advised adopted adopting the well used aridity index ( $\varphi$ ,  $= E_p/P$ , where  $E_p$  denotes the potential
- 25 evapotranspiration) as a measurement of the aridity degree, (e.g., and defined  $\varphi > 2$  corresponds to as dry areas) and  $\varphi < 2$  as wet regions. Consequently, the pattern became " $\varphi > 2$ ,  $\Delta(P E) < 0$ ; whereas  $\varphi < 2$ ,  $\Delta(P E) > 0$ ". Nevertheless, the attempt to link  $\Delta(P E)$  with  $\varphi$  also failed, even in qualitative terms. However, the results, which were based on By analysing more than 300 combinations of various global hydrologic data sets containing both observed and modelled data, of which most are simulations at the grid scale, Greve et al. (2014) noted showed that only 10.8% of land areas robustly followed the adjusted
- 30 DDWW pattern. However, the failure in terms of P E does not necessarily signify the absence of the DDWW pattern in Q. There are three major reasons. First, simulated  $\Delta(P - E)$  based on grids may vary from the observed  $\Delta Q$  based on catchments. Second, because simulations feature large uncertainties Nevertheless, the study of Greve et al. (2014) still has some defects related to two major aspects: one is the existence of large uncertainties in E in both the satellite-based

observations and the simulations (Kumar et al., 2016), especially for values of *E*, the estimated  $\Delta(P - E)$  may have much greater uncertainty than the measured  $\Delta Q$ . Third, the study of Greve et al. (2014) only ruled out his version of the DDWW pattern, whereas a slightly different DDWW pattern may be more appropriate. and the other is artificially assigned threshold between the wet and dry regions, which, when the threshold is changed, changes the results. Therefore, a study based on

5 observed <u>Ostreamflow</u> data <u>that are more direct and of relatively low uncertainty</u> should be conducted <u>as well as a new</u> <u>method to partition dry and wet regions not depending on the appointed threshold</u>. As this study focuses on the effects of elimate changes, the data should be restored to conditions without the influence of human activities, such as withdrawal and drainage (Stahl et al., 2010).

However, Aanother problem arises in the process of studying the observed Q data: the observed changes in Q are not only

- 10 responses to climate change but are also responses to other factors, such as land cover changes and human activities, e.g., withdrawal and drainage (Stahl et al., 2010). To extract the components related only to climate change is an intractable process because there is no effective method to do so. Therefore, a roundabout means is adopted by comparing the credibly estimated changes in *Q* under the influence of climate change with those of the observed data. Once a high correlation is verified between them, the observed changes in *Q* can be mainly attributed to climate change, and the presenting pattern is
- 15 <u>therefore a response to climate change</u>, proposing a new DDWW pattern involving the fact that the physical mechanism behind the original version does not exist anymore, meaning a feasible framework needs to be proposed for interpretation. The Budyko hypothesis (Budyko, 1948) is a robust and simple tool that can accurately model mean annual *Q* within a catchment based only on meteorological information under climate change believed to accurately describe the relationship between runoff and hydro-meteorological elements within a catchment by estimating the proportion of *P* transformed into *Q*
- 20 using a single equation that depends only on  $\varphi$  (Koster and Suarez, 1999). Details of the Budyko hypothesis are shown in Section 2.2. The Budyko hypothesis depicts the long-term coupled water-energy balance for a catchment as  $\overline{E}/\overline{P} = f(\overline{E_p}/\overline{P}, c),$  (1)

where the function f denotes Budyko-like equations,  $\overline{E_p}$  is the mean annual potential evapotranspiration, and c is a parameter characterizing a particular catchment. There are various types of Budyko-like equations (e.g., Pike, 1964; Fu, 1981;

- 25 <u>Choudhury, 1999; Zhang et al., 2001; Yang et al., 2008; Wang and Tang, 2014; Zhou et al., 2015).</u> The Budyko hypothesis has been examined and applied into both observation-based (Zhang et al., 2001; Oudin et al., 2008; Xu et al., 2014) and <u>simulationmodel</u>-based studies (Zhang et al., 2008; Teng et al., 2012) and produces good consistency between observed and <u>modelled data</u>. By analysing <u>hydro-meteorological</u> data from 108 nonhumid catchments in China, Yang et al. (2007) confirmed that the Budyko hypothesis is capable of predicting <u>Orunoff</u> both at long-term and annual time scales.
- 30 Xiong and Guo (2012) assessed the Budyko hypothesis in 29 humid watersheds in southern China and found that parametric Budyko formulae can estimate the long-term average Q<del>runoff</del> well. Therefore, the use of the Budyko hypothesis is reasonable in China.for depicting the relationship between Q and  $\varphi$  in China. The ability to capture the effects of climate change on Q and other details of the Budyko hypothesis are described in Section 2.3.

Based on <u>observed</u>a restored streamflow data <u>set of from</u> 291 catchments in China, and <u>comprehensive hydro-</u> meteorological data, this study first analyses <u>the historical trends in annual O</u>, exploring the possible existence of a DDWW pattern via a new method proposed in Section 2.2. the relationship between the streamflow trend and the aridity index to explore a feasible DDWW pattern. Then, adopting a simple framework derived from the Budyko hypothesis <u>stated in</u>

5 Section 2.3, this study estimates the runoff trends caused by climate change in the study catchments, revealing that the historical trends are mainly a response to climate change and identifying the key influencing factor. in the study catchments and interprets the mechanism of the DDWW pattern. Moreover, according tobased on the Coupled Model Intercomparison Project Phase 5 (CMIP5) projections of five GCMs, for the given framework, this study predicts changes in *Q* via the framework runoff to determine whether the DDWW pattern will continue to still hold in the future.

#### 10 2 Data and methods

#### 2.1 Study area and data-available

This study collected hydrologic and meteorological data from 291 catchments in mainland China,—with drainage areas ranging from 372 to 142,963 km<sup>2</sup>. These catchments include all the first level basins of mainland China except the Huaihe River Basin, and their distribution is shown in **Figure 1**. Annual <u>restored</u> discharge data from 1956 to 2000 for each

- 15 catchment outlet were provided by the Hydrological Bureau of the Ministry of Water Resources of China. <u>Here, "restored"</u> means the effects of human activities on the runoff in catchments, e.g., water withdrawals and reservoir regulations, have been mostly removed via certain technical means. Thus, the restored discharge can be considered the natural discharge (or very close). The records range in length from 21 years to 45 years, and 261 catchments have record lengths greater than 40 years. The shortest record length is 21 years, while the longest is 45 years, and 261 catchments have a record length greater
- 20 than 40 years. The annual areal precipitation and potential evapotranspiration for each catchment were calculated according to the 10 km gridded data set that was interpolated by Yang et al. (2014) based on 736 stations of the China Meteorological Administration.

<u>Two meteorological data sets were used in this study. One is the 10 km gridded data set interpolated by Yang et al. (2014)</u> based on 736 stations of the China Meteorological Administration, including P and potential evapotranspiration ( $E_p$ )

- 25 observations from 1956 to 2000. Based on this observed data set, the annual areal P and E<sub>p</sub> of each catchment were calculated. The other is the Ddaily bias-corrected (see Piani et al., 2010 and Hagemann et al., 2011) modelledelimate data set from the Inter-Sectoral Impact Model Intercomparison Project (ISI-MIP, http://www.isi-mip.org) covering the period 1951–2050, as projected by the CMIP5 under scenarios RCP2.6, RCP4.5 and RCP8.5, are adopted. Historical data for each model are used up to the year 2000, and the data then split into three representative concentration pathways (RCPs). These
- 30 <u>modelled</u> data <u>awe</u>re initially downscaled to a 0.5°×0.5° latitude–longitude grid by the Inter Sectoral Impact Model Intercomparison Project (ISI MIP, <u>http://www.isi mip.org</u>)-then extracted and transformed into the ASCII format by the Institute of Environment and Sustainable Development in Agriculture, the Chinese Academy of Agricultural Sciences, China.

The <u>output</u> data <u>of for</u> each scenario include simulations of precipitation; mean, maximum and minimum air temperature; solar radiation; wind speed; and relative humidity for five models (GFDL-ESM2M, HadGEM2-ES, IPSL-CM5A-LR, MIROC-ESM-CHEM and NorESM1-M). Historical data for each model is used up to the year 2000, and the data then split into three representative concentration pathways (RCPs). Using catchment boundaries to clip the data, catchment averaged

- 5 meteorological data are acquired. The daily potential evapotranspiration of each catchment is then estimated by the Penman Equation (Penman, 1948). By adding up the daily precipitation and potential evapotranspiration over the course of a year, this study generates annual series of P and  $E_p$  for each catchment. The gridded daily  $E_p$  is estimated based on the GCM outputs by the Penman Equation (Penman, 1948; see Appendix A for more details). By summing the daily P and  $E_p$  over the course of a year, this study generates annual series of P and  $E_p$ . Then, using catchment boundaries to clip the data, annual
- 10 catchment-averaged P and  $E_p$  data are acquired.

#### 2.2 <u>Runoff trends and the DDWW pattern To find a workable DDWW pattern</u>

Two crucial elements in the DDWW pattern are the definitions of "dry" ("wet") and "drier" ("wetter"). Since we focus on changes in runoff, the terms "drier" and "wetter" can be expressed as the runoff trend  $(k_Q)$  or change in mean annual runoff between 2 periods ( $\Delta \overline{Q}$ ). The parameter  $k_Q$  is adopted in studies based on continuously observed data (Section 3.1 and 3.2), whereas  $\Delta \overline{Q}$  is introduced in Section 3.3 to compare projected and observed data. The term  $k_Q$  can be calculated using the following linear regression: In this study, two slightly different definitions of the runoff trends are adopted for the historical data.

(1956-2000) and projected period (2001-2050). The runoff trend for the historical period is defined as the slope of the linear regression of the annual Q series, denoted by  $k_Q$ , and can be calculated by

$$k_{\mathcal{Q}} = \frac{\sum_{i=1}^{m} (t_i - \overline{t})(\mathcal{Q}_i - \overline{\mathcal{Q}})}{\sum_{i=1}^{m} (t_i - \overline{t})^2}, \tag{2}$$

15

 $k_{\vec{Q}} = \frac{\sum_{i=1}^{\#} (t_i - \vec{i}) (Q_i - \vec{Q})}{\sum_{i=1}^{\#} (t_i - \vec{i})^2},$ (2)

where  $\underline{mn}$  is the observed record length of a catchment, *i* is the *i*th record,  $t_i$  is the year of this record,  $\overline{t}$  is the average of all record years, and as  $Q_i$  and  $\overline{Q}$  are the observed runoff in  $t_i$  and the mean annual runoff in historical period, respectively. The significance of  $k_Q$  is determined using a t-test. The runoff trend of the projected period is denoted by  $\Delta \overline{Q}$ , defined as the change in mean annual runoff between historical and projected period, and can be computed as follows: The term  $\Delta \overline{Q}$  can be

25 calculated as follows:

$$\Delta \overline{Q} = \overline{Q}_{p} - \overline{Q}, \qquad (3)$$

where  $\overline{Q}_p$  denotes is the projected mean annual runoff. The introduction of  $\Delta \overline{Q}$  is necessary because  $k_Q$  is only appropriate for an identical sample, meaning that calculating the  $k_Q$  of an integrated sample including historical and projected data is not possible. Additionally, the  $k_Q$  of only the projected period fails to describe the change between the historical and future conditions, which is contrary to our purpose. Therefore,  $\Delta \overline{Q}$  is adopted as a way to compare projections with observations. However, because the GCMs cannot provide the projection of  $\overline{Q}_p$  directly,  $\Delta \overline{Q}$  was estimated based on a framework that will be introduced in Section 2.3. To define dry or wet condition, this study follows previous studies in introducing the aridity index  $\varphi$ . This work therefore focuses on finding an appropriate threshold to distinguish "dry" and "wet". The failure of the

5 commonly used threshold " $\varphi$ =2" in deriving a workable DDWW pattern (Greve et al., 2014) implies that the definition of aridity here is distinct from its meteorological definition; thus, a feasible threshold should be determined from the observed data. This study will plot the observed  $k_Q$  and  $\varphi$  relation curve and further search for a suitable threshold to find a workable pattern (Section 3.1).

In the study of Greve et al. (2014), the DDWW pattern is sensitive to the partition between the dry and wet regions because the partition depends on an assigned threshold separating the study areas, which leads to different (possibly conflicting) results depending on different thresholds. To remove the influence of the threshold, the study of Allan et al. (2010) adopted percentile bins for *P* to define wet and dry regions, thereby successfully avoiding the pitfalls of selecting a convincing threshold. Therefore, this study does not define absolute "wet" or "dry" regions but instead identifies relative "wetter" or "drier" ones. To be specific, two variables are chosen to be the indicators of the aridity index, <u>O</u> and  $\varphi_s$ 

- 15 respectively. The term  $\varphi$  is introduced to maintain consistency with studies based on the climate model data where  $\overline{Q}$  is not available. The spatial distribution of  $\overline{Q}$  and  $\varphi$  are shown in **Figure 2**, with  $\overline{Q}$  ranging from 0 to 1400 mm a<sup>-1</sup> and  $\varphi$  ranging from 0.5 to 8. We divide  $\overline{Q}$  and  $\varphi$  into six intervals, the intervals with larger  $\overline{Q}$  values and smaller  $\varphi$  values are wetter levels. The details are listed in **Table 1**. The sum of the catchments and the number of increasingly wetter catchments in each interval are used to calculate the proportion of wetter catchments in a given interval, denoted by *d*. A larger *d* value implies
- 20 <u>that more catchments have become wetter in this level. This study compares the *d* values of different intervals to examine a <u>new DDWW pattern.</u></u>

#### 2.3 A framework to estimate runoff trends under climate changeand interpret the DDWW pattern

25

In the long term, e.g., decades, water storage changes ( $\Delta S$ ) in the water balance can be reasonably neglected, and the mean annual precipitation ( $\overline{P}$ ) in a catchment can be partitioned into evapotranspiration ( $\overline{E}$ ) and runoff ( $\overline{Q}$ ). The Budyko hypothesis depicts the long term coupled water energy balance for a particular catchment as

## $\overline{E}/\overline{P} = f(\overline{E_p}/\overline{P}, c), \tag{3}$

where the function f denotes Budyko like equations,  $\overline{E_p}$  is the mean annual potential evapotranspiration,  $\overline{P}$  is the mean annual precipitation,  $\overline{E_p}/\overline{P}$  is the long term mean aridity index, and c is a parameter characterizing a particular catchment.

Among various types of Budyko-like equations (e.g., Pike, 1964; Fu, 1981; Choudhury, 1999; Zhang et al., 2001; Yang et al., 2008; Wang and Tang, 2014; Zhou et al., 2015), two analytical equations proposed by Fu (1981) and Yang et al. (2008) should be highlighted. Because these two studies each introduce a catchment property parameter, *ω* and *n*, respectively (two

<u>examples of c in Equation (1)</u>), these the two equations are able to better capture the role of landscape characteristics. Yang et al. (2008) showed a high linear correlation between  $\omega$  and n. Therefore, this study chooses the equation derived by Yang et al. (2008), which has been rewritten as follows and rewrites it as follows:

$$\frac{\overline{E}}{\overline{P}} = \left[ \left( \frac{\overline{E_p}}{\overline{P}} \right)^n + 1 \right]^{-1/n}.$$
(4)

5 Focusing on runoff, this study transforms Equation (4) into

$$\overline{Q} = \overline{P} - \overline{P} \left[ \left( \frac{\overline{E_p}}{\overline{P}} \right)^n + 1 \right]^{-1/n}.$$
(5)

The parameter *n* can be calibrated using observed  $\overline{Q}$ .  $\overline{P}$  and  $\overline{E}_p$  hydro-meteorological data available for<u>of</u> each catchment from the period of 1956 to 2000. The differential form of Equation (5) is derived as follows: Although derived from a long-term balance, this Budyko based model has been extended to annual estimates in many studies (Yang et al. 2007; Potter and

10 Zhang 2009; Yu et al. 2014). Therefore, the annual runoff can be estimated by

$$Q = P - (E_{p}^{-n} + P^{-n})^{-1/n}.$$
(6)

The differential form of Equation (6) can be expressed as follows:

$$-dQ = \frac{\partial Q}{\partial P}dP + \frac{\partial Q}{\partial E_{\rm p}}dE_{\rm p} + \frac{\partial Q}{\partial n}dn .$$
(6)

where dQ, dP, dE<sub>p</sub> and dn denote deviations in the observed or modelled Q, P, E<sub>p</sub> and n with respect to long-term mean
 value. Equation (<u>67</u>) has widely been used to estimate changes in <u>annual Qrunoff</u> (e.g., Arora, 2002; Fu et al., 2007; Yang and Yang, 2011; Roderick and Farquhar, 2011; Roderick et al., 2014).

Since we focus on the effects of climate change, n is assumed to remain unchanged, i.e., dn equalling 0 (Yang and Yang, 2011), and Equation (6) becomes As this study is concentrated on the influence of climate changes, the catchment characteristics are assumed to remain unchanged, and n is assumed to be constant (dn = 0) (Yang and Yang, 2011). Taking

20 the long term average condition as the balanced state for a catchment, any observed deviation from the balanced condition then can be estimated by

$$\Delta Q = c_P \Delta P + c_0 \Delta E_p, \tag{8}$$

$$dQ = \frac{\partial Q}{\partial r} dP + \frac{\partial Q}{\partial r} dE_p. \tag{7}$$

For convenience, we introduce  $\varepsilon_P$  and  $\varepsilon_0$  to represent  $\frac{\partial Q}{\partial E_p}$ , which can be estimated based on n,  $\overline{P}$  and  $\overline{E_p}$ ; where  $\Delta Q$ ,  $\Delta P$ 

25 and  $\Delta E_p$  are deviations from the balanced conditions and  $c_p$  and  $c_0$  are sensitivity coefficients, which can be estimated based on the catchment properties (*n*) and the long term mean precipitation and potential evaporation:

$$\varepsilon_P = \frac{\partial Q}{\partial P}\Big|_{(\overline{P}, \overline{E_p})} = 1 - \left[1 + \left(\frac{\overline{E_p}}{\overline{P}}\right)^{-n}\right]^{\frac{n+1}{n}}$$
 and

$$\varepsilon_0 = \frac{\partial Q}{\partial E_{\rm p}} \bigg|_{(\overline{P}, \overline{E_{\rm p}})} = -\left[1 + \left(\frac{\overline{E_{\rm p}}}{\overline{P}}\right)^n\right]^{\frac{n+1}{n}}$$

Roderick et al. (2014) showed that the runoff changes (= $\Delta(P - E)$  in this study) estimated using Equation (7) account for around 82% of the variation in the GCM projections of  $\Delta(P - E)$ . Therefore, Equation (7) can predict a reliable result under climate change projected by GCMs. Based on Equation (78), a framework can then be constructed to estimate runoff trends  $k_{CI}$  or  $\Delta\overline{Q}$  (see Appendix B for interpretation):

$$k_{Qe} = \varepsilon_P k_P + \varepsilon_0 k_{E_p},$$

$$\Delta \overline{Q}_e = \varepsilon_P \Delta \overline{P} + \varepsilon_0 \Delta \overline{E_p},$$

$$k_Q = c_P k_P + c_\theta k_{E_p},$$
(8a)

$$\Delta Q = c_P \Delta P + c_0 \Delta E_p, \tag{8b}$$

10 where  $k_{Qe}$  and  $\Delta \overline{Q}_e$ ,  $k_{\overline{\mu}}$  and  $k_{\overline{k_p}}$  are estimated runoff trends of the historical and projected period, respectively; in precipitation and potential evapotranspiration that are also calculated by the linear regression,  $k_P$  and  $k_{E_p}$  are the linear regressioncalculated trends in annual P and  $E_p$ , respectively; and  $\Delta \overline{P}$  and  $\Delta \overline{E_p}$  are changes in  $\overline{P}$  and  $\overline{E_p}$ , respectively. mean annual precipitation and potential evapotranspiration.

This framework can explicitly elucidate how the DDWW pattern works, namely how  $\varphi$  affects  $k_Q$ . Equation (8a) and 15 (8b)(9a) attributes the runoff trend to two major parts (one attributed to the trend in *P* and the other attributed to the trend in  $E_p$ ) factors, the precipitation trend and the potential evapotranspiration trend. and the effects of their per unit change on the runoff trend are quantified by  $\varphi$ . In Section 3.2,  $k_Q$  is estimated using observed  $k_P$  and  $k_{E_p}$ . Once a high correlation is found

between the estimated and observed  $k_{Q}$  values, the DDWW pattern can be interpreted by the Budyko hypothesis. Equation (8a) estimates  $k_{Qe}$  according to the observed  $k_P$  and  $k_{E_p}$ . Equation (8b) estimates  $\Delta \overline{Q}_e$  according to the GCM projections, and

- 20  $\Delta \overline{P}$  and  $\Delta \overline{E_p}$  are calculated as differences in  $\overline{P}$  and  $\overline{E_p}$  between 1956–2000 and 2001–2050. In Section 3.3, the DDWW pattern is further assessed in projections. The values of  $\Delta \overline{Q}$  are estimated by Equation (9b) according to projected changes in elimatic variables based on the CMIP5 scenarios.  $\Delta \overline{P}$  and  $\Delta \overline{E_p}$  in Equation (9b) are calculated as changes in mean annual values from 1956–2000 to 2001–2050. Due to the uncertainty of the GCMs, Tthe coefficient of variance (C<sub>v</sub>) in each catchment is estimated, which is defined as the ratio between the standard deviation and the absolute mean values, is
- 25 estimated from the outputs of the five GCMs to measure the uncertainty of the projections. The  $C_v$  is defined as the ratio between the standard deviation and the absolute mean of the five  $\Delta \overline{Q}_e$  outputs of the respective GCMs. Specifically, a lower  $C_v$  indicates less uncertainty in  $\Delta \overline{Q}_e$  because the results of the different GCMs are similar, and the direction of relative change is more convincing.

#### 3 Results and discussion

#### 3.1 Historical trends in annual runoffTesting the DDWW pattern in historical trends

**Figure 32** presents the spatial distribution of <u>observed  $k_0$  runoff trends</u> in the 291 study catchments. At the significance level of 0.05, 39.9% (116 of 291) of the study catchments are undergoing significant changes in <u>annual *O*runoff</u> and are called

- 5 "significant catchments" in the following text. Trends towards wetter <u>conditions</u> (positive trends) are found mainly in the upper and lower reaches of the Yangtze River basin, the Southwest and the Southeast Rivers basin, the Pearl River basin and the Inland Rivers basin. <u>The annual *Q*Streamflow</u> in the lower reaches of the Yangtze River basin and the Northern Xinjiang Uygur Autonomous Region is robustly increasing by over 2 mm a<sup>-1</sup>, which is greater than the rates of most other catchments. The largest increasing trend of 10.3 mm a<sup>-1</sup> is observed in the Yangtze River basin. However, <u>the catchments in the middle</u>
- 10 reaches of the Yangtze River basin and in northern and northeastern China are experiencing the greatest reductions in runoff, generally with significant trends. Several catchments have negative trends of over 4 mm a<sup>-1</sup>, and the most severe situation is observed-in the Yellow River basin, where the annual *Q*runoff is decreasing at a rate of 7.2 mm a<sup>-1</sup>.

The relationship between runoff trends  $k_Q$  and  $\overline{Q}$  the corresponding  $\varphi$  for all the studied catchments is plotted in the left column of Figure 43, which also shows the *d* for each interval. With increasing  $\overline{Q}$ , *d* increases from 0.18 to 0.88, meaning

- 15 that "drier regions are more likely to become drier, whereas wetter regions are more likely to become wetter". The slight decrease in d to 0.79 in the last interval can be attributed to the small sample size of this interval, as the number of catchments getting drier is actually equal in intervals 5 and 6 (Table 2). Therefore, a new DDWW pattern is derived based on the analysis of the observed data. This pattern emphasizes the fact that the distribution of water resources has become more uneven in China since 1950s. The process driving the uneven distribution of water resources in this study is powerful
- 20 because nearly all the wettest catchments became wetter and the driest catchments became drier. whereas the right column shows only the conditions of the significant catchments. However, in both situations, if we adopt the threshold of Greve et al. to partition dry and wet regions (Figure 3(c) and (d)). Unfortunately, the DDWW pattern of those authors does not work well in China and results in a success rate of only 60%. However, by setting the threshold equal to 1, a feasible DDWW pattern can be proposed, where  $k_Q>0$  if  $\varphi<1$ , and vice versa. 78.4% of study catchments (228) follow the new pattern, and among the
- 25 significant catchments, the ratio climbs to 90.5% (105 of 116, 14 with  $\varphi$ <1). Specifically, 76.3% of wet regions (71 of 93) and 79.3% of dry regions (157 of 198) are consistent with the pattern. For the significant catchments, 8 of the 11 failure cases are located in dry regions.

Moreover, to introduce the DDWW pattern into studies based on climate model data where  $\overline{Q}$  is not available, an analysis of  $k_Q$  and  $\varphi$  is also performed. Figure 5 shows that d decreases from 0.86 to 0.16 as  $\varphi$  increases, implying that the DDWW

30 pattern also holds if we adopt  $\varphi$  to describe the aridity degree, similar to Greve et al. (2014). This relationship is explained by **Figure 6a**, in which a monotonic decrease in  $\overline{Q}$  with  $\varphi$  is revealed. However, *d* increases sharply to 0.36 in the last interval, in contrast to the DDWW pattern. To understand this divergence, we have marked areas with  $\varphi$ >2 and  $k_{Q}$ >0 (26 in total) in **Figure 6b.** Surprisingly, most of these areas (19 of 26) are located in areas with glaciers. Therefore, the changes in water storage ( $\Delta S$ ) from the melting of glacial ice and snow also play a key role in the runoff generation there. However,  $\varphi$  does not consider the influence of  $\Delta S$ , thereby leading to an overestimation of the aridity degree in these catchments, i.e., they are in the wrong intervals. This reflects the weakness of the ability of  $\varphi$  to assess the aridity degree with respect to water

5 resources compared to Q. Moreover, if we can acquire specific ΔS information, by redefining an adjustable aridity index (φ') as (P - ΔS)/E<sub>p</sub>, the failure of the DDWW pattern in areas with high φ is not expected to exist anymore.
 The finding of the DDWW pattern in China has led us to review the study of Greve et al. (2014) and realize the

probability of the worldwide existence of the DDWW pattern. Based on a threshold ( $\varphi$ =2) to identify wet and dry regions, Greve et al. noted that the traditional summary "dry get drier, wet get wetter" does not hold over land between the periods

- 10 <u>1948-1968 and 1985-2005</u>. After removing transitional areas that cannot be definitely identified as wet or dry, the percentages of the four types, i.e., wet-wetter (WW), wet-drier (WD), dry-wetter (DW) and dry-drier (DD), computed via Figure 4c for the residual areas (Greve et al., 2014) are 21%, 42%, 5% and 32%, respectively. Unfortunately, Greve et al. did not provide detailed information on  $\varphi$  for the study regions, and we therefore cannot examine the DDWW pattern directly as we did for the observed data. However, to elucidate the possibility of the DDWW pattern over land, we can simply assume a
- 15 special situation as in Figure 7. Each shape denotes one type of regions (WW, WD, DW and DD) in Greve et al. (2014), and the area in a small interval represents the count of respective regions, with the total area representing the sum of this type. In this situation, the DDWW pattern apparently holds as *d* decreases when  $\varphi$  increases. Certainly, to ensure the existence of the DDWW pattern globally, a subsequent study that includes the distribution of  $\varphi$  across the world is necessary.

#### 3.2 Interpreting the trends from climate change perspectivepattern using the Budyko hypothesis

- Based on a comparison of the Budyko-estimated  $_{Qe}$  with observed  $k_Q$  trends with the observed trends, the coefficients of determination ( $R^2$ ) (Legates and McCabe, 1999) are 0.70 and 0.86 for all catchments and for significant catchments, respectively (**Figure <u>84</u>**), which means Equation (6) accurately estimates the trends via a simplified consideration of Therefore, the majority of the runoff trends can be attributed to changes in the atmospheric forcing of water and energy. Moreover, because the DDWW pattern is a qualitative description, it focuses more on the signs of the trends. In **Figure 4**,
- 25 However, the slope k is smaller than one (0.60 and 0.62 for all catchments and significant catchments, respectively), implying that the Budyko-based framework underestimates the changes in runoff. Since the framework only quantifies the effects of climate change, the estimated deviation may stem from the neglect of other influencing factors, such as ecological and environmental changes, that result in changes in the catchment properties (*dn* in Equation 6) that we assume to be constant in this study. Nevertheless, despite underestimating the runoff trends, the framework can correctly note the direction
- 30 <u>of runoff changes in more than 80% of the study catchments (Figure 8), as the error rates (proportions of misestimated catchments that have different signs of observed and estimated trends) in all and significant catchments are 18.6% (54 of 291) and 6.0% (7 of 116), respectively, meaning that the Budyko hypothesis can correctly predict the direction of runoff changes</u>

in more than 80% of the study catchments. Furthermore, the DDWW pattern works well based on  $k_{Qe}$  (Figure 9), which validates the DDWW pattern from the perspective of climate change based on historical meteorological observations. It also indicates the feasibility of using only *P* and  $E_p$  information to examine the pattern, and serves as a reference for studies based on climate model outputs. Therefore, the DDWW pattern based on streamflow observations can be interpreted as the response of runoff to the climate change

5 response of runoff to the climate change.

In catchments where the observed and the estimated signs are consistent, the part of  $k_{Qe}$  the runoff trend generated from  $\underline{P}$  $(k_{Q_2}^p = \varepsilon_P k_P)$  and  $E_p$   $(k_{Q_2}^0 = \varepsilon_0 k_{E_p})$  precipitation  $k_Q^p$   $(= \varepsilon_P k_P)$  and potential evapotranspiration  $k_Q^0$   $(= \varepsilon_0 k_{E_p})$  are compared to find the factor controlling the runoff changes due to climate change. As shown in Figure 10,  $k_P$  Precipitation makes an overwhelming contribution in 88.6% (210 of 237) of these catchments, resulting in as ratios of absolute  $k_Q^0$  to absolute  $k_Q^0$ 

- 10 that are smaller than 1 (Figure 5). This result can add an instance to the study of Roderick et al. (2014) based on the GCM outputs (CMIP3), of which a significant conclusion is that the changes in water availability ( $\Delta(P E)$ ) are dominated by the changes in *P* ( $\Delta P$ ) globally. In the remaining catchments, two thirds are located in wet areas. This simple analysis implies that the DDWW pattern is mainly a response of runoff to precipitation changes, emphasising the significance of the Budyko hypothesis to identifying the controlling factor in the DDWW pattern. Furthermore, when using Budyko estimated trends to
- 15 test the DDWW pattern, the proportion of catchments following the pattern is 73.5% (214 of 291), which is quite close to the observed proportion (78.7%). Therefore, the Budyko hypothesis a suitable method for assessing the DDWW pattern when observed streamflow data are not available. Moreover, when linking  $k_P$  with  $\overline{Q}$  (Figure 11), we observe a pattern similar to the DDWW pattern, i.e., "more precipitation in wetter areas, and less in drier areas". This pattern is the result of the dominant position of  $k_P$  and the positive effect of  $k_P$  on the runoff trends. Therefore, from the perspective of climate change,
- 20 the more uneven precipitation results in more uneven runoff, producing the DDWW pattern.

## 3.3 Predicting future trends using the GCM projections Assessing the pattern in the future scenarios

Based on the GCM projections, equation (8b) predicts the future runoff trends  $\Delta \overline{Q}_e$  Great discrepancies appear in predicted  $\Delta \overline{Q}_e$  between the periods of 1956–2000 and 2001–2050 among the five different models, even under the same scenario (Figure 6 left). The results show that great discrepancies appear in  $\Delta \overline{Q}_e$  among the five GCMs even under the same scenario,

- 25 whereas the model-averaged results under different scenarios are close (Figure 12). In particular, tThe C<sub>v</sub> values of  $\Delta \overline{Q}_e$  the predicted  $\Delta \overline{Q}$  in each catchment are presented in Figure 13Figure 6-right. Taking the RCP2.6 scenario as an example, over two-fifths (41.9%) of the catchments have a C<sub>v</sub> value larger than 0.5, which is indicative of the great uncertainty in the various models reported by previous studies (e.g., Greve et al., 2014; Kumar et al., 2016). In contrast, only slight distinctions arise among the results predicted by the same model under different scenarios. Therefore, different elimate scenarios actually
- 30 induce a consistent pattern in future runoff changes. However, the proposed DDWW pattern is no longer suitable <u>under three</u> scenarios, regardless of which model is selected, because *d* decreases as  $\overline{Q}$  increases, except for an increase in interval 6, in

contrast to the DDWW pattern. It can be speculated that the failure of the DDWW pattern doesn't mean an obvious alleviation of the uneven water resource distribution but conveys a bad news that most areas of China (over 60%, calculated from **Table 3**) will experience water resource shortages under the projected climate changes, whereas the changes in the conditions of the driest (interval 6) and wettest (interval 1) areas are relatively slight. Furthermore, a process similar to that

- 5 described in Section 3.2 is performed to identify the main meteorological factor controlling the future trends. As shown in **Figure 14**, trends in  $P(\Delta \overline{P})$  are no longer the controlling factor, as only 40% of the catchments have values of  $\left|\frac{\epsilon_0 \Delta \overline{E_p}}{\epsilon_p \Delta \overline{P}}\right|$  smaller than 1. Note that this result is based on the mean values of the five GCMs. Considering the mean of the five models' results for the scenarios RCP2.6, RCP4.5 and RCP8.5, the proportions of catchments following the DDWW pattern are 40.2% (117), 43.0% (125) and 40.5% (118), respectively. Unlike clearly separating the catchments with differing trends as in the historical
- 10 analysis, the threshold  $\varphi$ =1 cannot distinguish the projected changes. In fact, according to this partition, nearly 80% of wet catchments ( $\varphi$ <1) become drier and experience a decrease in mean annual runoff, whereas over half of the dry areas ( $\varphi$ >1) experience increasing runoff.

The spatial distribution of model-averaged relative changes in  $\overline{Q}(\Delta \overline{Q}_{e}/\overline{Q})$  mean annual runoff is shown in **Figure 157**. The results under the three scenarios are similar. Red regions are catchments where  $\overline{Q}$  mean annual runoff will fall more than 60% relative to the historical value, and most of these regions are located in the Yellow River Basin with relatively high certainty (C<sub>v</sub><0.5). The most severe situation arises in a catchment situated in the Yangtze River Basin, where the runoff is predicted to be nearly zero and the C<sub>v</sub> is even less than 0.2. In contrast On the contrary, dark blue areas are catchments where  $\overline{Q}$  is whose runoff is projected to increase by over 40%. These catchments are primarily located in the Inland River Basin, glacier areas, except for Northwest China, where catchments will suffer from a shortage of fresh water. Instead of continuing to

- 20 become drier, catchments in Northeast and North China are projected towill generate more runoff in the future, whereas catchments in the lower reaches of the Yangtze River Basin will experience considerable reductions in runoff, despite <u>historicalprevious</u> increases. These <u>patterns</u> are the most obvious distinctions between the projected and historical runoff changes and directly result in the failure of the DDWW pattern. Thus, the DDWW pattern fails to accurately characterize these future patterns.
- 25 <u>However, an inevitable concern about the GCM outputs is their uncertainty, which determines the reliability of the</u> projected results. To examine the uncertainty, one workable method is to compare meteorological observations with simulations for the period of 1956–2000. Taking the results of the GFDL-ESM2M model as an example (**Figure 16**),  $\overline{P}$  is simulated well except for some obvious incorrectly estimated points far from the y = x line. However, simulations of  $\overline{E_p}$ show tremendous deviations, resulting in no obvious linear relationship between the simulated and observed values. This
- 30 <u>simple comparison directly highlights the unreliability of the GCM outputs. Although uncertainties also exist in observations</u> due to observational errors associated with the relevant variables, such as air temperature, solar radiation and wind speed, the

obvious differences between the observed and simulated values of  $\overline{E_p}$  should be mainly attributed to the GCM outputs. These findings also demonstrate that further improvements in the GCMs are necessary.

#### **4** Discussion

#### **4.1 Evaluation of the DDWW pattern**

- 5 The DDWW pattern is shown to be valid in the majority of study catchments (Section 3.1). However, catchments in the Inland River basin and the Southwest Rivers basin do not follow the pattern if examined spatially (Figure 8). Although situated in dry areas (φ>1), the streamflow increases in nearly all catchments in these areas. The common factor is that the streamflow in each catchment originates from glaciers, meaning that changes in water storage (ΔS) also play a key role in runoff generation. Therefore, these catchments differ from other catchments that rely only on precipitation. Consequently,
- 10 the melting of glacial ice and snow due to global warming is one possible factor resulting in the pattern failure. Because the aridity index identifies wet and dry regions based on precipitation, the proposed pattern is therefore only appropriate for catchments in which runoff is primarily derived from precipitation.

This emphasises again the significance of selecting a suitable criterion for defining wet and dry conditions in the DDWW pattern. Considering the influence of  $\Delta S$ , redefining an adjustable aridity index ( $\phi$ ) as ( $P - \Delta S$ )/ $E_{p}$  may better describe the

- 15 aridity degree if  $\Delta S$  data are available. Moreover, the threshold of the aridity index should also be set appropriately. In the study of Greve et al.,  $\varphi$ =2 does not produce a suitable pattern for China. In this study, the study catchments in China were indeed found to follow the DDWW pattern by setting  $\varphi$ =1 as the threshold. However, 40% of the continental areas still obey the DDWW pattern of Greve et al., suggesting that the appropriate threshold for a given region varies worldwide. This observation explains why the attempts of previous studies to obtain a unified pattern based on a single threshold failed. The
- 20 threshold of different areas can be regarded as a parameter in the globally unified DDWW pattern.

#### **4.2 Further discussion of the framework**

Since Equation (8) is type of a linear combination of  $\Delta P$  and  $\Delta E_{p}$ , indexes before these two variables can also be determined using the linear regression (Zheng et al., 2009). By assuming these two variables are independent for simplicity, the indexes can be regarded as the simple linear regression coefficients between the respective variable and  $\Delta Q$  as follows:

25 
$$e'_{P} = \frac{\sum \Delta P_{i} \Delta Q_{i}}{\sum \Delta P_{i}^{2}}$$
 and

$$\varepsilon_{\theta}' = \frac{\sum \Delta E_{pi} \Delta Q_i}{\sum \Delta E_{pi}^2},$$

where  $c'_{\mu}$  and  $c'_{0}$  are estimates of sensitivity coefficients and  $\Delta P_{i}$  and  $\Delta E_{pi}$  are yearly deviations in the long term average precipitation and potential evapotranspiration, respectively. Then, the runoff trend can be estimated by

The estimated results are shown in **Figure 9**. Compared to the estimates of Equation (9a) (**Figure 4 left**), the slope and  $R^2$  are 0.57 and 0.66, respectively, both of which are relatively smaller than those of Equation (9), suggesting that Equation (9a) yields better estimates on runoff changes.

- 5 However, the slope k is smaller than one (**Figure 4**, 0.60 and 0.62 for all catchments and significant catchments, respectively), implying that the Budyko hypothesis underestimates changes in runoff. Part of the estimated deviation may stem from the neglect of other influencing factors, such as catchment property changes and human activities, while the remaining deviation is related to aspects of *P* and  $E_p$  that cannot be captured by Equation (9a) due to their implicit expression or coupling with other factors.
- 10 Moreover, the low error rates of Equation (9a) discussed in Section 3.2 suggest that it can be used to explore why the DDWW pattern is applicable to natural conditions at the large scale (e.g., in China). By transforming Equation (9a) into

$$\frac{\Delta Q}{\Delta E_{p}} = c_{p} \frac{\Delta P}{\Delta E_{p}} + c_{0}, \tag{11}$$

 $\frac{\Delta Q}{\Delta E_{p}}$  can be expressed as a function of  $\frac{\Delta P}{\Delta E_{p}}$ ,  $\varphi$  and *n*. Since the DDWW pattern is related to the sign of  $\Delta Q$ , it is important to

determine the combination of  $\frac{\Delta P}{\Delta E_p} \varphi$  and *n* values that lead to the critical situation in which  $\Delta Q$  equals zero. In this critical

## 15 situation, the relationships among these three variables can be written as

$$c_{\rm P} \frac{\Delta P}{\Delta E_{\rm p}} + c_{\rm 0} = 0.$$
<sup>(12)</sup>

Therefore, the critical value of  $\frac{dH^2}{AF_m}$  under a given  $\varphi$  and *n* can be expressed as

$$\frac{\Delta P}{\Delta E_{\rm p}} = \frac{\epsilon_{\rm p}}{\epsilon_{\rm p}} = \frac{\left[1 + \left(\frac{E_{\rm p}}{P}\right)^{\frac{n+1}{n}}\right]^{\frac{n+1}{n}}}{1 - \left[1 + \left(\frac{E_{\rm p}}{P}\right)^{\frac{n}{n}}\right]^{\frac{n+1}{n}}}.$$
(13)

To separate the effect of  $\varphi$ , it is appropriate to use a fixed value for *n*. **Figure 10** plots critical values of  $\frac{\Delta P}{\Delta E_p}$  for different combinations of  $\varphi$  and *n*. Curves with larger *n* values plot to the right of curves with smaller *n* values. Each curve divides the zone into two parts. If an observed  $\frac{\Delta P}{\Delta E_p}$  is larger than the critical value, i.e., the data point plots above the curve,  $\Delta Q$  will be greater than zero when  $\Delta E_p$  is positive and less than zero when the latter is negative. If  $\frac{\Delta P}{\Delta E_p}$  is smaller than the critical value, the results will be the opposite.

Based on the plot of measured  $\frac{\Delta P}{\Delta E_p}$  values in Figure 11, 64.7% and 77.3% of catchments with  $\Delta E_p > 0$  and  $\Delta E_p < 0$ 

25 O strictly meet the DDWW pattern, and the overall ratio for all the catchments is 65.6%. In this context, "strictly" means  $\frac{\Delta P}{\Delta E_{p}}$ is larger than the highest possible value (when *n* is set as the maximum of study catchments) or smaller than lowest possible value (when *n* is set as the minimum of study catchments). This result suggests that there may be other influencing factors that make the actual  $\frac{\Delta P}{\Delta E_{p}}$  values widely different from the theoretical critical values, making the validity of the DDWW pattern quite strong in China.

#### 4.3 Failure of the DDWW pattern in projections

- 5 In the analysis of future runoff changes, projected meteorological data from GCMs are used. Therefore, to evaluate the reliability of the projections, observed meteorological data was compared with historical modelled data for the same period of 1956–2000. Taking the results of the GFDL-ESM2M model as an example (**Figure 12**), mean annual precipitation is simulated well except for some obvious incorrectly estimated points far from the y = x line. However, simulations of mean annual potential evapotranspiration show tremendous deviations, resulting in no obvious linear relationship between the
- 10 modelled and observed values. This simple comparison thus directly highlights the unreliability of the assessment of the DDWW pattern in projections. Although there also exist uncertainties in observation, originated from observational errors of relevant variables, such as air temperature, solar radiation and wind speed, the obvious distinctions between the observed and the projected values of  $E_{\rm P}$  should be mainly attributed to the unreliability of the projection. Since Equation (9b) predicted  $\Delta \overline{Q}$  based on the modelled  $\Delta \overline{P}$  and  $\Delta \overline{E_{\rm P}}$ , unreliable  $\Delta \overline{P}$  and  $\Delta \overline{E_{\rm P}}$  data consequently lead to unreliable  $\Delta \overline{Q}$  estimates. Therefore, a
- 15 possible cause of why the DDWW pattern does not hold in the future is the low reliability of the projections, and the conclusion in Section 3.3 should be adopted with caution. These findings also demonstrate that further improvements in the GCMs are necessary.

#### **45** Conclusions

- Based on the analysis of restored streamflow in 291 catchments across China from 1956 to 2000, wetting trends were found
  mainly in the upper and lower reaches of the Yangtze River basin, Southwest and Southeast China and the Inland River basin, whereas drying trends were found in the catchments in the middle reaches of the Yangtze River basin and in North and Northeast China. Based on a combination of observed streamflow and meteorological data, a suitable DDWW pattern is revealed: "catchments with an aridity index *q*<1 become wetter, and catchments with an aridity index *q*>1 become drier". Approximately 80% of all studied catchments and over 90% of catchments that have a significant trend (*p* = 5%) in runoff followed this relationship. However, notably, catchments in glacier regions (the Inland Rivers basin and the Southwest
- Rivers basin) did not follow the pattern, possibly because the melting of snow and ice has significant effects on runoff generation. By relating  $k_0$  to  $\overline{Q}$ , a suitable DDWW pattern is revealed: "*drier regions are more likely to become drier*, *whereas wetter regions are more likely to become wetter*", implying that the distribution of the water resources in China has become more uneven since the 1950s. This study adopts  $\varphi$  as an indicator of water availability, which is similar to most
- 30 researches on climate change based on GCMs, and validates the DDWW pattern in all the catchments except for those

located in glacier regions with large  $\varphi$  values, where  $\Delta S$  plays a significant role in the runoff generating. Moreover, as seen from the perspective of the new DDWW pattern, the study of Greve et al. (2014) may also support this finding, and the uneven trend is likely a global phenomenon.

A framework based on the Budyko hypothesis was introduced to interpret the DDWW pattern from the perspective of

- 5 <u>climate change</u>estimate runoff changes. The high correlation between  $k_{Qe}$  and  $k_Q$  the Budyko estimated trends and the observed trends demonstrates that the runoff changes can be mainly attributed to the changes in the atmospheric forcing of water and energythe DDWW pattern can be interpreted by the Budyko hypothesis. Although the framework-Notably, the Budyko hypothesis underestimated the runoff trends, possibly due to the neglect of other natural influencing factors leading to catchment property changes, it can correctly indicate the direction of runoff changes in more than 80% of the study
- 10 <u>catchments</u>, such as catchment property changes and human activities, or the failure to fully capture *P* and  $E_p$ . Moreover, this framework reveals that precipitation is the controlling factor in climate changes that result in the DDWW pattern in China, as demonstrated by nearly 90% of catchments where observed and estimated signs are consistent. Additionally, the DDWW pattern is applicable based on  $k_{Qe}$ , indicating the feasibility of using the framework to assess the pattern. Furthermore, this framework reveals that  $k_P$  is the controlling factor associated with climate change, and the finding of a pattern similar to the
- 15 DDWW pattern in k<sub>P</sub> indicates that increasingly uneven precipitation results in increasingly uneven runoff. According to the projections of five <u>GCMsmodels</u> (GFDL-ESM2M, HadGEM2-ES, IPSL-CM5A-LR, MIROC-ESM-CHEM and NorESM1-M) from CMIP5, this study predicted <u>future</u> changes in <u>Q</u> under three scenarios (RCP2.6, RCP4.5 and RCP8.5) - mean annual runoff. Simulations under different scenarios (RCP2.6, RCP4.5 and RCP8.5) showed similar results, whereas significant differences are present among the models. Significant differences are present among the different
- 20 <u>models.</u> However, the proposed DDWW pattern is no longer suitable, regardless of <u>which model is selected</u> the projected situation, as the proportion of catchments becoming wetter decreases as  $\overline{Q}$  increases only 40% of the catchments follow this pattern. Nearly 80% of the wet catchments ( $\varphi$ <1) will become drier, while over half of the dry areas ( $\varphi$ >1) will become wetter. Unfortunately, the model-average results suggest that over 60% of catchments will experience water resource shortages under future climate change, and the *P* trends ( $\Delta \overline{P}$ ) will no longer be the controlling factor in runoff changes, as
- 25 <u>only 40% of the study catchments will be primarily controlled by  $\Delta \overline{P}$ , which is different from the phenomenon that the runoff change was controlled by precipitation in about 90% catchments in the historical period. The Catchments in Northeast and North China, which were becoming drier, will generate more runoff in future, whereas the: In contrast, catchments in the lower reaches of the Yangtze River Basin, which were becoming wetter, will experience considerable reductions in runoff. These changes represent the most obvious differences between the projected and historical runoff</u>
- 30 <u>changes. Thus, the DDWW pattern fails to explain the future changes.</u> Nevertheless, <u>the above<del>this</del> conclusions</u> remains tentative due to the <u>enormous</u> unreliability of the <u>GCM outputs as indicated by the extremely low correlations between the</u> <u>simulated and observed</u>  $\overline{E_p}$  values for the period of 1956–2000model projections. The considerable differences between the observed and modelled meteorological data for the same period suggest that the prediction should be adopted with caution.

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## Appendix A

	The procedure for using the Penman Equation to estimate $E_{p}$ (mm d <sup>-1</sup> ) based on the GCM outputs is described in detail in
	this appendix. The Penman Equation can be written as (Yang et al., 2011)
	$E_{\rm p} = \frac{0.408\Delta(R_n - G) + 2.624\gamma(1 + 0.536u_2)(1 - \rm RH)e_{\rm s}}{\Delta + \gamma},\tag{A.1}$
5	where $e_s$ is the saturated vapor pressure (kPa), $\Delta$ is the slope of the saturated vapour pressure versus air temperature curve
	(kPa °C <sup>-1</sup> ) when the saturated vapour pressure equals $e_{ss}R_n$ is the net radiation (MJ m <sup>-2</sup> d <sup>-1</sup> ), G is the soil heat flux (MJ
	$m^{-2} d^{-1}$ , y is a psychometric constant (kPa °C <sup>-1</sup> ), $u_2$ is the wind speed at a height of 2 m (m s <sup>-1</sup> ), and RH is the relative
	humidity (%) (Yang et al., 2011).
	The form of the saturated vapour pressure versus air temperature curve is
10	$e(T)=0.6108\exp(\frac{17.27T}{T+237.3}),$ (A.2)
	where T denotes the daily air temperature, and $e_s$ of the day can be calculated by
	$e_s = \frac{e(T_{\text{max}}) + e(T_{\text{min}})}{2},$ (A.3)
	where $T_{\text{max}}$ and $T_{\text{min}}$ are maximum and minimum daily air temperatures, respectively.
	The GCM outputs are daily $T_{\text{max}}$ , $T_{\text{min}}$ (which can be used to calculate $e_s$ and $\Delta$ ), $u_2$ and RH. Assuming G equals 0 and if
15	we compute $R_n$ , we can use Equation (A.1) to estimate $E_p$ . The process of utilizing the solar radiation ( $R_s$ ) to compute $R_n$ is
	described below.
	Firstly, we calculate the incoming net short wave radiation $(R_{ns})$ by
	$R_{\rm ns} = (1 - \alpha) R_{\rm s} $ (A.4)
	where $\alpha$ denotes the albedo.
20	Next, the net outgoing long-wave radiation $(R_{nl})$ is estimated by
	$R_{\rm nl} = \sigma \left(\frac{T_{\rm max}^4 + T_{\rm min}^4}{2}\right) \left(0.34 - 0.14\sqrt{e_a}\right) \left(1.35\frac{R_s}{R_{s0}} - 0.35\right),\tag{A.5}$
	where $\sigma$ is the Stefan–Boltzmann constant (=4.903×10 <sup>-9</sup> MJ K <sup>-4</sup> m <sup>-2</sup> day <sup>-1</sup> ), $e_a$ is the actual vapour pressure (= $e_s$ × RH), and
	$R_{s0}$ is the clear-sky solar radiation, which can be computed by
	$R_{s0} = (0.75 + 2 \times 10^{-5} z) R_a, \tag{A.6}$
25	where z is the station elevation above sea level (m), which is available from the GCMs, and $R_a$ is the extraterrestrial radiation
	(MJ m <sup>-2</sup> d <sup>-1</sup> ) determined by Equations (21) to (25) in Allen et al. (1998).
	<u>Finally, by subtracting <math>R_{nl}</math> from <math>R_{ns}</math>, we obtain <math>R_{n}</math>.</u>

## Appendix **B**

This appendix provides an explicit <u>description</u>elucidation of the derivation of the framework for estimating  $k_Q$  and  $\Delta \overline{Q}$  from Equation (8). Substituting Equation (8) into Equation (2) yields

$$k_{Q} = \frac{\sum_{i=1}^{mn} (t_{i} - \bar{i})(\varepsilon_{P} \Delta P_{i} + \varepsilon_{0} \Delta E_{pi})}{\sum_{i=1}^{mn} (t_{i} - \bar{i})^{2}} \,. \tag{B.1}$$

5 This equation can be transformed into

$$k_{Q} = \varepsilon_{P} \frac{\sum_{i=1}^{mn} (t_{i} - \bar{t}) \Delta P_{i}}{\sum_{i=1}^{mn} (t_{i} - \bar{t})^{2}} + \varepsilon_{0} \frac{\sum_{i=1}^{mn} (t_{i} - \bar{t}) \Delta E_{pi}}{\sum_{i=1}^{mn} (t_{i} - \bar{t})^{2}}.$$
(B.2)

Recalling the definition of the trend in this study, Equation (BA.2) can be considered a linear combination of  $k_P$  and  $k_{E_p}$ ,

namely:

 $k_Q = \varepsilon_P k_P + \varepsilon_0 k_{E_p}$ .

10 Equation  $(\underline{32})$  can be rewritten as

$$\Delta \overline{Q} = \frac{\sum_{i=1}^{m_{i}} Q_{pi} - m_{ii} \overline{Q}}{m_{ii}}.$$
(B.3)

Recombination of the variables leads to the following expression:

$$\Delta \overline{Q} = \frac{\sum_{i=1}^{m} (\mathcal{Q}_{pi} - \overline{Q})}{m} \,. \tag{B.4}$$

Similarly, the substitution of Equation (8) yields

$$15 \quad \Delta \overline{Q} = \frac{\sum_{i=1}^{m} (e_P \Delta P_i + e_Q \Delta E_{pi})}{m}.$$
(B.5)

We finally obtain the target equation:

 $\Delta \overline{Q} = \varepsilon_P \Delta \overline{P} + \varepsilon_0 \Delta \overline{E_p} \,.$ 



Figure 1: Spatial distribution of the 291 study catchments over mainland China.



Figure 2: Spatial distribution of mean annual runoff  $\overline{Q}$  (left) and aridity index  $\varphi$  (right) in the 291 study catchments.



Figure <u>32</u>: The observed runoff trends[ $k_Q$ ] in the 291 catchments for the period of <u>1956</u> to <u>2000</u>. Dark red and blue adenote catchments with a trend smaller than -6 mm a<sup>-1</sup> and larger than 8 mm a<sup>-1</sup>, respectively. Crosshatched areas are significant catchments(<u>p7</u>). Grey <u>shaded shading</u> areas are glaciers based on the second glacier inventory dataset of China (Guo et al., 2014).



Figure 3: Relationship between observed runoff trends and aridity index for all catchments (left column) and significant catchments (right column). Aridity index is plotted in the logarithmic coordinate. The threshold is set as 1 in (a) and (b), while in (c) and (d) as 2 according to Greve et al. (2014). WW signifies that catchments with φ smaller than the threshold value have positive trends in runoff, whereas WD have negative trends. DD means positive trends in runoff in areas where φ is larger than the threshold, whereas DW negative trends. Percentage is the proportion of each kind.



Figure 4: Relationship between observed runoff trends  $k_Q$  and mean annual runoff  $\overline{Q}$  for the study catchments (left) and values of *d* in each interval according to  $\overline{Q}$  (right). *d* denotes the proportion of catchments with positive trends in each interval. Interval numbers 1 to 6 correspond to six intervals 0–200, 200–400, 400–600, 600–800,800–1000 and 1000–1400.



Figure 5: Relationship between observed runoff trends  $k_Q$  and mean annual runoff  $\overline{Q}$  for the study catchments (left) and values of d in each interval according to  $\varphi$  (right). Interval numbers 1 to 6 correspond to six intervals 0.5–2/3, 2/3–1, 1–1.5, 1.5–2,2–3 and 3–8.



Figure 6: Relationship between mean annual runoff  $\overline{Q}$  and aridity index  $\varphi$  in the study catchments (left) and the distribution of catchments with  $\varphi \ge 2$  and  $k_0 \ge 0$  (right). Grey shaded areas are glaciers based on the second glacier inventory data set of China (Guo et al., 2014).



**Figure 7: Diagram of a special condition of Greve et al. (2014) to make the DDWW pattern work.** Blue, orange, green and red shapes denote 4 types of regions (WW, WD, DW and DD) in the previous study, with the areas denoting respective sums of each type according to the respective proportions (21%, 42%, 5% and 32%). For each shape, the area in a small interval denotes the number of respective regions, and the *d* of the interval is calculated by the ratio of the area of the shape over the  $k_Q$ =0 line to the total area of shape in the interval. In this situation, the DDWW pattern apparently holds, as *d* decreases as  $\varphi$  increases.





Figure <u>84</u>: Comparison of estimated runoff trends  $k_{Qe}$  with observed <u>ones\_trends  $k_Q$  (left)</u>for (a) all catchments and (<u>rightb</u>) significant catchments. Significant catchments are ones undergoing significant changes in runoff at the significance level of 0.05. Error <u>The error</u> rate is defined as the proportion of <u>misestimated</u> catchments <u>in which the that have different</u> signs between the observed and the estimated trends <u>differ</u>.



Figure 9: Relationship between observed runoff trends  $k_{Qe}$  and mean annual runoff  $\overline{Q}$  for the study catchments (left) and values of *d* in each interval according to  $\overline{Q}$  (right). Interval numbers 1 to 6 correspond to six intervals 0–200, 200–400, 400–600, 600–800,800– 1000 and 1000–1400.



5 Figure 105: Exploring the controlling factor in the DDWW pattern according to the Budyko hypothesis. (left) Relationship between the ratio of absolute  $k_Q^0$  (= $\varepsilon_0 k_{E_p}$ , the part of the runoff trend  $k_{Qe}$  generated from the potential evapotranspiration changes) to absolute  $k_Q^p$  (= $\varepsilon_P k_P$ , the part of  $k_{Qe}$  the runoff trend generated from the precipitation changes) and the mean annual runoff  $\overline{Q}$  aridity index  $\varphi$ . (right) The cumulative frequency curve of  $|k_Q^0/k_Q^p|$ .



Figure 11: Relationship between observed runoff trends  $k_P$  and mean annual runoff  $\overline{Q}$  for the study catchments (left) and values of <u>*d* in each interval according to  $\overline{Q}$  (right). Interval numbers 1 to 6 correspond to six intervals 0–200, 200–400, 400–600, 600–800,800–</u> 1000 and 1000-1400.





Figure 12: Projections of future trends  $\Delta \overline{Q}_e$  under (top) RCP2.6, (middle) RCP4.5 and (bottom) RCP8.5 scenarios for the period 2001-2050. (left column) Relationship between projected  $\Delta \overline{Q}_e$  of the five models and their means and mean annual runoff  $\overline{Q}$ . (right column) Values of *d* in each interval according to  $\overline{Q}$  based on  $\Delta \overline{Q}_e$  of the five models and their means. Interval numbers 1 to 6 correspond to six intervals 0–200, 200–400, 400–600, 600–800,800–1000 and 1000–1400.

× GFDL-ESM2M + HadGEM2-ES = IPSL-CM5A-LR + MIROC-ESM-CHEM • NorESM1-M



**Figure 6:** Assessment of the DDWW pattern under (a) RCP2.6, (b) RCP4.5 and (c) RCP8.5 Scenarios. (left) Relationship between predicted changes in mean annual runoff ( $\Delta \overline{Q}$ ) of five models and the aridity index. (right) Coefficient of variance ( $C_{\nu}$ ) of predicted runoff changes. Each blue point denotes a catchment.



Figure 13: C<sub>v</sub> values of projected future trends  $\Delta \overline{Q}_e$  under (left) RCP2.6, (middle) RCP4.5 and (right) RCP8.5 Scenarios.



Figure 14: Exploring the controlling factor in the projected climate change under (left) RCP2.6, (middle) RCP4.5 and (right) RCP8.5.



Figure <u>157</u>: Spatial distribution of the model-averaged relative changes in the mean annual runoff  $\overline{Q} (= \Delta \overline{Q_c}/\overline{Q})$  for the period of <u>2001 to 2050</u> under three different scenarios. Hatched areas denote regions with C<sub>v</sub> values smaller than 0.5, whereas double-d-hatched areas represent regions with C<sub>v</sub> values smaller than 1.



Figure 8: Spatial examination of the DDWW pattern from 1956 to 2000. Grey shading areas are glaciers based on the second glacier inventory dataset of China.



5 Figure 9: Comparison of the runoff trends estimated by Equation (7) with the observed trends for all catchments.



**Figure 10: (left)** Critical values of  $\frac{\Delta P}{\Delta E_p}$  (making  $\Delta Q$  equal 0) in different combinations of  $\varphi$  and *n*. (**right**) Schematic diagram of examining the DDWW pattern. The threshold line ( $\varphi$ =1, black) and the critical curve of  $\frac{\Delta P}{\Delta E_p}$  (green) divide the combinations of observed  $\frac{\Delta P}{\Delta E_p}$  and  $\varphi$  into 4 parts, where  $\Delta Q$  in I and II will be larger than 0 if  $\Delta E_p$  is positive, and vice versa, while the situation in III and IV is conversed. According to the DDWW pattern, all the feasible situations following it will be located in zones I and IV when  $\Delta E_p$ >0, whereas in zones





Figure 11: Observed values of  $\frac{\Delta P}{\Delta E_p}$ . Curves of critical  $\frac{\Delta P}{\Delta E_p}$  values with largest *n* (=4.94) of all catchments and smallest *n* (=0.25) are presented in green and blue correspondingly. Each point denotes an observed  $\frac{\Delta P}{\Delta E_p}$  of a special catchment. Specifically, red points denote catchments that not only obey the DDWW pattern but also are with  $\frac{\Delta P}{\Delta E_p}$  values larger than the maximum of possible critical value (*n*=4.94) or smaller than the minimum (*n*=0.25). Considering critical value of  $\frac{\Delta P}{\Delta E_p}$  ranges from 0 to 1, measured ones larger than 1 are set as 1, whereas ones smaller than -0.1 are set as -0.1(to be better separated from values close to 0).



Figure 12: Comparison of the observed meteorological data with the simulations from the GFDL-ESM2M model for <u>the period</u> 1956—2000.

Table 1: Details of the interval partitions based on mean annual runoff  $\overline{Q}$  and aridity index  $\varphi_{-}$ 

Interval number	<b>Interval range</b>	Sample size					
Based on $\overline{Q}$							
<u>1</u>	<u>0-200</u>	<u>141</u>					
<u>2</u>	200-400	<u>42</u>					
<u>3</u>	400-600	<u>31</u>					
<u>4</u>	<u>600-800</u>	<u>26</u>					
<u>5</u>	800-1000	<u>32</u>					
<u>6</u>	<u>1000-1400</u>	<u>19</u>					
Based on <i>\varphi</i>							
<u>1</u>	0.5-2/3	<u>21</u>					
<u>2</u>	2/3-1	<u>72</u>					
<u>3</u>	<u>1-1.5</u>	<u>33</u>					
<u>4</u>	<u>1.5-2</u>	<u>55</u>					
<u>5</u>	<u>2-3</u>	<u>68</u>					
<u>6</u>	<u>3-8</u>	<u>42</u>					

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Table 2: Number of catchments with $ko > 0$ and respective d in each interval based on $\overline{O}$	and <i>o</i> in	the analysis of	the observed trends.

Table 2: Number of catchments with <i>ko</i> >0 and respect								
Interval	d							
<u>number</u>	<u>with <i>ko</i>&gt;0</u>	<u>u</u>						
Based on $\overline{Q}$								
<u>1</u>	<u>26</u>	<u>0.18</u>						
<u>2</u>	<u>11</u>	<u>0.26</u>						
<u>3</u>	<u>12</u>	<u>0.39</u>						
<u>4</u>	<u>20</u>	<u>0.77</u>						
<u>5</u>	<u>28</u>	<u>0.88</u>						
<u>6</u>	<u>15</u>	<u>0.79</u>						
Based on <i>\varphi</i>								
<u>1</u>	<u>18</u>	<u>0.86</u>						
<u>2</u>	<u>53</u>	<u>0.74</u>						
<u>3</u>	<u>6</u>	<u>0.18</u>						
<u>4</u>	<u>9</u>	<u>0.16</u>						
<u>5</u>	<u>11</u>	<u>0.16</u>						
<u>6</u>	<u>15</u>	<u>0.36</u>						

	<u>Interval</u> number	1	2	<u>3</u>	<u>4</u>	5	<u>6</u>	
<u>RCP2.6</u>								
GEDI ESM2M	Number	<u>74</u>	<u>12</u>	<u>6</u>	<u>6</u>	<u>13</u>	<u>12</u>	
<u>OFDE-ESW2W</u>	<u>d</u>	<u>0.52</u>	0.29	<u>0.19</u>	0.23	<u>0.41</u>	<u>0.63</u>	
HadGEM2 ES	Number	<u>76</u>	<u>12</u>	<u>9</u>	<u>5</u>	<u>9</u>	<u>12</u>	
HauOEWI2-ES	<u>d</u>	<u>0.54</u>	0.29	<u>0.29</u>	<u>0.19</u>	0.28	<u>0.63</u>	
IPSL-CM5A-	Number	<u>86</u>	<u>13</u>	<u>8</u>	<u>2</u>	<u>4</u>	<u>3</u>	
LR	<u>d</u>	<u>0.61</u>	<u>0.31</u>	<u>0.26</u>	<u>0.08</u>	<u>0.13</u>	<u>0.16</u>	
MIROC-ESM-	Number	<u>93</u>	<u>16</u>	<u>9</u>	<u>5</u>	<u>6</u>	<u>4</u>	
<u>CHEM</u>	<u>d</u>	<u>0.66</u>	<u>0.38</u>	<u>0.29</u>	<u>0.19</u>	<u>0.19</u>	<u>0.21</u>	
N. TOMI M	Number	<u>75</u>	<u>14</u>	<u>8</u>	<u>7</u>	<u>11</u>	<u>13</u>	
<u>NOTESIMI-IM</u>	<u>d</u>	<u>0.53</u>	0.33	<u>0.26</u>	<u>0.27</u>	<u>0.34</u>	<u>0.68</u>	
Madal and a	Number	<u>80</u>	<u>13</u>	<u>6</u>	<u>5</u>	<u>7</u>	<u>8</u>	
Model-averaged	<u>d</u>	<u>0.57</u>	<u>0.31</u>	<u>0.19</u>	<u>0.19</u>	<u>0.22</u>	<u>0.42</u>	
			RCI	<u>94.5</u>				
GEDL-ESM2M	Number	<u>62</u>	<u>8</u>	<u>3</u>	<u>6</u>	<u>10</u>	<u>11</u>	
<u>GIDE ESMEM</u>	<u>d</u>	<u>0.44</u>	<u>0.19</u>	<u>0.10</u>	<u>0.23</u>	<u>0.31</u>	<u>0.58</u>	
HadGEM2-ES	Number	<u>72</u>	<u>11</u>	<u>8</u>	<u>7</u>	<u>9</u>	<u>10</u>	
	<u>d</u>	<u>0.51</u>	0.26	<u>0.26</u>	<u>0.27</u>	<u>0.28</u>	<u>0.53</u>	
IPSL-CM5A-	Number	<u>77</u>	<u>13</u>	<u>8</u>	<u>3</u>	<u>6</u>	<u>6</u>	
LR	<u>d</u>	<u>0.55</u>	<u>0.31</u>	0.26	<u>0.12</u>	<u>0.19</u>	<u>0.32</u>	
MIROC-ESM-	Number	<u>97</u>	<u>20</u>	<u>11</u>	<u>5</u>	<u>8</u>	<u>5</u>	
<u>CHEM</u>	<u>d</u>	<u>0.69</u>	<u>0.48</u>	<u>0.35</u>	<u>0.19</u>	<u>0.25</u>	<u>0.26</u>	
NovESM1 M	Number	<u>60</u>	<u>16</u>	<u>6</u>	<u>8</u>	<u>8</u>	<u>10</u>	
<u>INOLESIVIT-IVI</u>	<u>d</u>	<u>0.43</u>	<u>0.38</u>	<u>0.19</u>	<u>0.31</u>	<u>0.25</u>	<u>0.53</u>	
Model averaged	Number	<u>71</u>	<u>13</u>	<u>6</u>	<u>5</u>	<u>7</u>	<u>7</u>	
wiouer-averaged	<u>d</u>	0.50	<u>0.31</u>	<u>0.19</u>	<u>0.19</u>	0.22	<u>0.37</u>	
<u>RCP8.5</u>								
GFDL-ESM2M	Number	84	<u>11</u>	<u>6</u>	4	8	<u>6</u>	

<u>Table 3: Numbers of catchments with  $\Delta \overline{Q}_{e} \ge 0$  and respective *d* in each interval based on  $\overline{Q}$  of five GCMs and their means in the analysis of the projected trends under three scenarios.</u>

	<u>d</u>	<u>0.60</u>	0.26	<u>0.19</u>	<u>0.15</u>	<u>0.25</u>	<u>0.32</u>
HadGEM2 ES	Number	<u>75</u>	<u>12</u>	<u>8</u>	<u>5</u>	<u>9</u>	<u>10</u>
Haddewiz-ES	<u>d</u>	<u>0.53</u>	0.29	0.26	<u>0.19</u>	0.28	0.53
IPSL-CM5A-	Number	<u>71</u>	<u>10</u>	<u>6</u>	<u>3</u>	<u>5</u>	<u>4</u>
LR	<u>d</u>	<u>0.50</u>	<u>0.24</u>	<u>0.19</u>	<u>0.12</u>	<u>0.16</u>	<u>0.21</u>
MIROC-ESM-	Number	<u>76</u>	<u>17</u>	<u>6</u>	<u>5</u>	<u>5</u>	<u>4</u>
<u>CHEM</u>	<u>d</u>	<u>0.54</u>	<u>0.40</u>	<u>0.19</u>	<u>0.19</u>	<u>0.16</u>	<u>0.21</u>
NorESM1 M	Number	<u>74</u>	<u>11</u>	<u>6</u>	<u>6</u>	<u>7</u>	<u>10</u>
	<u>d</u>	<u>0.52</u>	<u>0.26</u>	<u>0.19</u>	<u>0.23</u>	0.22	<u>0.53</u>
Model averaged	Number	<u>75</u>	<u>13</u>	<u>6</u>	<u>4</u>	<u>6</u>	<u>6</u>
<u>iviouei-avelageu</u>	<u>d</u>	<u>0.53</u>	<u>0.31</u>	<u>0.19</u>	<u>0.15</u>	<u>0.19</u>	0.32