Assessments of joint hydrological extreme risks in a warming climate in China

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ABSTRACT: Understanding how hydrological extremes would respond to global warming and its associated uncertainties is important for better designing mitigation and adaption strategies to cope with global change. Very few works have investigated the changes in future hydrological extremes and, especially, the more devastating joint hydrological extremes over China. In this article, two combinations of joint extremes [i.e. high runoff/high soil moisture (HRHS) and low runoff/low soil moisture (LRLS)] are designed for analysis. To derive the scenarios of hydrological conditions, the bias-corrected daily climate projections from five global circulation models (GCMs) under the historical and Representative Concentration Pathways 8.5 (RCP8.5) emission scenarios are used to drive the calibrated Variable Infiltration Capacity (VIC) model from 1951 to 2099 over China. Results show notable increase of occurrence of HRHS in Northeast China, LRLS in Northwest and South of China under 2 °C global warming. The spatial pattern of changes in joint extremes tends to remain stable with global temperature increase up to 3 °C. Compared with the individual extreme risk, joint extreme are much more concentrated in Northwest and South China and the magnitude of changes is several times larger. Larger areas experiencing changes are found when using lower standards of extreme definition. Because hydrological regime may change gradually in response to climate change, the threshold derived from present regime may lead to misrepresentation of extreme risk analysis. This was demonstrated by the ten times smaller magnitude of changes when adopting the updated transient threshold representing the changing hydrological regime, thus providing a low-boundary of potential changes in extremes. Our results highlight the importance of considering the changing hydrological regime in addition to choosing various levels of threshold for extreme definition in order to cover the full range of possible extreme changes in a warming climate.

KEY WORDS climate change; hydrological extreme; China

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1. Introduction

Hydrological extremes in the form of droughts and wet spells have devastating impacts on the environment and social society (Below *et al.*, 2007). With climate warming, not only the climatology but also the extreme would change (Arnell, 2003; O'Gorman and Schneider, 2009; Durack *et al.*, 2012; Kumar *et al.*, 2013a, 2013b). For better mitigation and adaptation strategies, decision makers require accessible and accurate information about the potential changes of hydrological extremes as well as the associated uncertainties (IPCC, 2012).

There is an extensive body of literature that documents the future climate change impact on the hydrological extremes. Most large-scale studies focus either on precipitation or soil moisture (e.g. Wang, 2005; Sheffield and Wood, 2008; Xu *et al.*, 2009; Dai, 2012; Vidal *et al.*, 2012;

Orlowsky and Seneviratne, 2013; Trenberth *et al.*, 2014) or runoff/streamflow related extremes (e.g. Hirabayashi *et al.*, 2013; Arnell and Gosling, 2014; Forzieri *et al.*, 2014; van Huijgevoort *et al.*, 2014). The limitations of these studies are that most of them focus on one single variable of interest for analysis. In fact, traditional extreme risk assessment relying on only one variable may not accurately represent the concurrent extremes which are more devastating to the society, economy and ecosystems, and would therefore lead to misrepresentation of the extreme risks. For example, drought may be characterized by not only low streamflow but also concurrent low soil moisture conditions. Hence, it is hypothesized that information revealed by the joint hydrological extremes may not be apparent in individual extreme analysis. And a multivariate viewpoint may provide additional and new insights in extreme risk assessments especially in a warming climate (Hao *et al.*, 2013; AghaKouchak *et al.*, 2014). Despite this, analysis of joint hydrological extremes is scarce and future joint hydrological extreme risks with climate warming are rarely investigated.

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Furthermore, most of previous studies investigated individual extreme changes on fixed future time periods (e.g. 2020s, 2050s or 2080s), making it difficult to compare the results as they are conducted under a wide range of scenarios. In fact, what is more relevant to policy maker is a complete picture of how regional impacts might accrue with specific global warming magnitudes such as the 2 °C limit as suggested by the European Union (Randalls, 2010).

In extreme events analysis, an important issue is the determination of extreme definition. Among various existing approaches, threshold methods (Hisdal *et al.*, 2001; Lorenzo-Lacruz *et al.*, 2013) are gaining increasing popularity. By this approach, extreme events are defined as occurring when the value of variable of interest is less than a given threshold. Most previous studies on large-scale future hydrological extremes (e.g. drought/floods) have applied the so-called fixed threshold method (e.g. Hirabayashi *et al.*, 2013; Arnell and Gosling, 2014; Dankers *et al.*, 2014; Prudhomme *et al.*, 2014). Typically, characteristics of extremes in the 21st century are identified by using the threshold derived from the fixed historical period (e.g. 1971–2000). However, this stationary approach ignored the gradual change of hydrological regime in response to climatic changes as predicted by global climate models (GCMs) (Durack *et al.*, 2012). In fact, the dry/wet conditions in the present may become normal in the future (Piontek *et al.*, 2014) and should not be recognized as the droughts/wet spells in the future. One may argue whether or not such a stationary approach is appropriate for the assessments of extreme risk changes with climate change. Therefore, how this additional source of uncertainty associated with impact assessments would affect the extreme risk analysis deserve further investigations.

China is a developing country and more vulnerable to hydrological extremes than developed countries (Piao *et al.*, 2010). A number of studies have reported the characteristics of historical hydrological extreme events across the country (e.g. Ma and Fu, 2003; Wang and Zhai, 2003; Zhai *et al.*, 2005; Zou *et al.*, 2005; Wang *et al.*, 2011; Wu *et al.*, 2011; Xu *et al.*, 2014). With global warming due to increase in greenhouse gases, it is very important to investigate the future possible changes in hydrological extremes over the country in order to facilitate the adaptation and mitigation strategies. Recently, assessments of future hydrological extremes have been conducted with a focus on specific river basins using climate scenarios from previous generation [i.e. Coupled Model Intercomparison Project Phase 3 (CMIP3)] of GCMs and emission scenario [i.e. Special Reports on Emission Scenarios by the Intergovernmental Panel on Climate Change (IPCC SRES)] (Xu *et al.*, 2009; Liu *et al.*, 2011; Guo *et al.*, 2013; Duan and Mei, 2014; Gu *et al.*, 2015). Very few works, however, have investigated the future hydrological extremes at the country scale (Leng *et al.*, 2015), and analysis of future concurrent hydrological extreme risks is especially scarce across the whole country.

Here, we use the newly bias-corrected CMIP5 climate projections to drive the large-scale Variable Infiltration

Capacity (VIC) model which was well calibrated against observations (Zhang *et al.*, 2014a) to derive the time series of future runoff and soil moisture conditions over China. We focus on the changes in joint extremes of the land surface hydrological components including runoff and soil moisture. In addition, an alternative updated threshold with a moving reference window designed to reflect the changing hydrological regime in response to climate change. By comparing with the results using traditional threshold methods, we attempt to show the uncertainties arising from the effects of the changing hydrological regime. We report the results as a function of global warming amount. In this article, Section 2 introduces the modelling method and analysis measures, Section 3 evaluate the risks of future joint extreme, and the uncertainties arising from the threshold definition and effects of changing hydrological regimes. Section 5 is for the conclusion and discussion of the main findings of this study.

2. Data and methodology

2.1. Bias-corrected climate change projections

Climate projections from five GCMs are obtained from the Inter-Sectoral Impact Model Inter-comparison Project (ISI-MIP, Warszawski *et al.*, 2014). The climate projections are bias corrected in terms of the variability and mean of the observed climate (WATCH forcing data, Weeden *et al.*, 2011) using the quantile-mapping approach (Hempel *et al.*, 2013). The climate projections are provided at $0.5^\circ \times 0.5^\circ$ spatial resolution at daily time step from 1950 to 2099 and include all the necessary meteorological variables for driving land surface hydrological models. In the framework of ISI-MIP, unfortunately, only five different GCMs under the newly developed representative concentration pathways (RCPs) were bias corrected in order to provide timely assessments for the IPCC AR5 reports when this study initiated (Moss *et al.*, 2010; Taylor *et al.*, 2012; Collins *et al.*, 2013). Hence, it should be noted that the full uncertainty range may not be covered and our results should only represent the potential changes by the 5 GCMs (see Table 1 for descriptions of the climate models). As found by previous studies (Tang and Lettenmaier, 2012; Gillett *et al.*, 2013; Zhang *et al.*, 2014b), global mean temperature (GMT) changes as an index characterizing the climate changes are independent of the emission pathways. Therefore, an example narrative assessment was presented in this study using the RCP8.5 scenarios to show the climate change impacts on the joint extremes. We acknowledge that regional climate projections may differ in terms of the magnitude of changes among the four RCPs even under the same level of GMT rise.

2.2. Simulation of future runoff and soil moisture conditions over China

The VIC model (Liang *et al.*, 1994, 1996) was adopted to simulate the runoff, evapotranspiration and soil moisture. The VIC model is a physically based, semi-distributed model and is featured with the sub-grid variability of

Table 1. Descriptions of five GCMs used in this study.

Model name	Institute acronyms	Institute full name
GFDL-ESM2M	NOAA GFDL	NOAA Geophysical Fluid Dynamics Laboratory
HadGEM2-ES	MOHC (additional realizations by INPE)	Met Office Hadley Centre and Instituto Nacional de Pesquisas Espaciais
IPSL-CM5A-LR	IPSL	Institut Pierre-Simon Laplace
MIROC-ESM-CHEM	MIROC	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies
NorESM1-M	NCC	Norwegian Climate Centre

vegetation, soil and terrain characteristics. The VIC model has been widely applied for assessing the climate change impacts on hydrology at regional and global scales (e.g. Nijssen *et al.*, 2001; Andreadis *et al.*, 2005; Sheffield and Wood, 2008; Shukla and Wood, 2008).

The information of soil texture and bulk densities is derived by combining the 5-min digital global soil map by the Food and Agricultural Organization (FAO, 1998) with the World Inventory of Soil Emission Potentials database (Batjes, 1995). Vegetation types are derived from the advanced very high resolution radiometer-based global land cover classifications (Hansen *et al.*, 2000). Six parameters, i.e. the three parameters in baseflow scheme (D_m : the maximum velocity that can occur from the lowest soil layer, D_s : the fraction of D_m where nonlinear base flow begins, W_s : the fraction of the maximum soil moisture of the lowest soil layer where nonlinear base flow occurs), the infiltration parameter b and the second and third soil layer depths (d_2 , d_3), were well calibrated for the ten river basins over China by optimizing the simulated streamflow against observations. Details for the model calibration and validation can be found in Zhang *et al.* (2014a). By using the above bias-corrected climate data, time series of daily hydrologic terms from the calibrated VIC model were produced for the period 1950–2099. We excluded the first 20-year results to eliminate the impact of initial conditions and started our analysis from 1971 to 2099.

2.3. Analysis measures

The 90 and 10% quantiles of monthly runoff and soil moisture in the historical period (1971–2000) are used as threshold levels for defining the extremes.

Specifically, the identification of future high runoff (HR) event is as follows:

$$HR(i, j, n) = \begin{cases} 1, & R(i, j, n) \geq R_x(t_0, n) \\ 0, & R(i, j, n) < R_x(t_0, n) \end{cases} \quad i = 1, 2, \dots, 30; j = 1, 2, \dots, 12 \quad (1)$$

where $HR(i, j, n)$ is a binary variable indicating whether a location or grid cell (n) is in extreme. i, j are for the year and month, respectively. $R_x(t_0, n)$ is the x (e.g. 90%) percentile threshold derived from the monthly values of the reference period (e.g. 1971–2000) centred at the year t_0 (e.g. 1985). For identification of low runoff events, the 10% percentile threshold is used.

$$LR(i, j, n) = \begin{cases} 1, & R(i, j, n) < R_x(t_0, n) \\ 0, & R(i, j, n) \geq R_x(t_0, n) \end{cases} \quad i = 1, 2, \dots, 30; j = 1, 2, \dots, 12 \quad (2)$$

Here, 90% quantiles indicates runoff or soil moisture occurrences above the 90% quantile, while 10% quantiles denotes occurrences below the 10% quantile. To examine the sensitivity of joint extremes to the choice of threshold levels, we select the 70 and 80% quantiles for defining the above-normal condition and 30 and 20% quantiles for the below-normal conditions, respectively.

Similarly, the identification of soil moisture extreme is as follows:

$$HS(i, j, n) = \begin{cases} 1, & S(i, j, n) \geq S_x(t_0, n) \\ 0, & S(i, j, n) < S_x(t_0, n) \end{cases} \quad i = 1, 2, \dots, 30; j = 1, 2, \dots, 12 \quad (3)$$

$$LS(i, j, n) = \begin{cases} 1, & S(i, j, n) < S_x(t_0, n) \\ 0, & S(i, j, n) \geq S_x(t_0, n) \end{cases} \quad i = 1, 2, \dots, 30; j = 1, 2, \dots, 12 \quad (4)$$

Two combinations of joint extremes are defined for detailed analysis: HRHS and LRLS, representing the number of concurrent high runoff/high soil moisture and low runoff/low soil moisture, respectively. In other words, joint extremes are defined as being concurrent abnormal conditions of both runoff and soil moisture. The identification of joint extremes is as follows:

$$HRHS(i, j, n) = \begin{cases} 1, & HR(i, j, n) = 1 \text{ and } HS(i, j, n) = 1 \\ 0, & HR(i, j, n) = 0 \text{ or } HS(i, j, n) = 0 \end{cases} \quad i = 1, 2, \dots, 30; j = 1, 2, \dots, 12 \quad (5)$$

$$LRLS(i, j, n) = \begin{cases} 1, & LR(i, j, n) = 1 \text{ and } LS(i, j, n) = 1 \\ 0, & LR(i, j, n) = 0 \text{ or } LS(i, j, n) = 0 \end{cases} \quad i = 1, 2, \dots, 30; j = 1, 2, \dots, 12 \quad (6)$$

It should be noted that there are some other indicators which may consider the combined hydrological

behaviours such as the Palmer Drought Severity Index (PDSI) and Standardized Precipitation Evapotranspiration Index (SPEI) (precipitation minus potential evapotranspiration). These types of indicators are characterized by merging multiply sources of information into one integrated index. The metrics HRHS and LRLS as used in this study, however, represent the concurrence of multiply extremes. That is, various single extremes overlapped at the specified spatial-temporal scale. Furthermore, the metrics used in this study explicitly include runoff that is distinct from the meteorological drought indicators based on precipitation and temperature. Hence, the metrics used in this study are different from those multi-variable indicators. To calculate the PDSI or SPEI is not within the scope of this study because we focus on the changes in the concurrence of single extremes of land surface water component (i.e. runoff and soil moisture).

There are generally two approaches to construct future climate scenarios representing specific global mean temperature change (ΔGMT). Tang and Lettenmaier (2012) selected those scenarios on future time periods when a given ΔGMT was exceeded. By this, the timing of the specific ΔGMT may be different among GCMs. The other approach is generally referred to as ‘pattern-scaling’ through constructing the linear relationship between specific amount of climate forcing and impacts (Gerten *et al.*, 2013; Arnell *et al.*, 2014). This approach is usually conducted at the monthly scale and thus may neglect the effects of variability changes. Also, the derived relationship may depend on the variables selected for the construction of relationship function. In this study, we adopted the approach proposed by Tang and Lettenmaier (2012) which has been widely used in a number of climate change impact studies (e.g. Portmann *et al.*, 2013; Haddeland *et al.*, 2014; Schewe *et al.*, 2014; Zhang *et al.*, 2014b) to construct the climate scenarios associated with specific ΔGMT .

For each grid n , the total number of joint extremes in the historical and future periods associated with specific global warming amount is first calculated. Then the percentage changes are calculated as follows:

$$\begin{aligned} \Delta\text{HRHS}(n) &= 100 \times \frac{\sum \text{HRHS}(i, j, n) - \sum \text{HRHS}(i_0, j_0, n)}{\sum \text{HRHS}(i_0, j_0, n)} \\ i &= 1, 2, \dots, 30; j = 1, 2, \dots, 12 \end{aligned} \quad (7)$$

$$\begin{aligned} \Delta\text{LRLS}(n) &= 100 \times \frac{\sum \text{LRLS}(i, j, n) - \sum \text{LRLS}(i_0, j_0, n)}{\sum \text{LRLS}(i_0, j_0, n)} \\ i &= 1, 2, \dots, 30; j = 1, 2, \dots, 12 \end{aligned} \quad (8)$$

It should be noted that the changes in the frequency (number of joint extreme events) rather than the magnitudes are investigated in this study. As for the dynamical (non-stationary) threshold approach, the threshold is

based on the monthly values of the previous 30-year time window (i.e. $t_0 = i - 1$). By this, threshold varies every year during the 21st century. In addition, this approach adjusts to the gradual changes in the hydrological regime in response to climate change. The percent changes in the joint occurrence of extremes are calculated for each simulation, and the multi-model ensemble is used for our analysis. Uncertainty ranges/magnitudes along with the multi-model ensemble mean results were presented by using the box-diagram scheme.

3. Results

3.1. Regional climatic change across China under 2 °C global warming

Figure 1 shows the multi-model ensemble mean changes in annual mean temperature and precipitation over China under the backdrop of 2 °C global warming. The magnitude of changes in regional temperature exhibits an evident geographical gradient where the increment of temperature increases from South China to North China. Notably, China is primarily characterized by the increment of temperature less than 2°, whereas only small parts of northern and western China will experience temperature increment higher than 2°. Compared with temperature increment, regional disparity is significant for the precipitation response to the 2 °C global warming. According to model projections, northwestern and northeastern China will experience an increase in precipitation by 5–10%, and the largest percentage increase (>15%) will occur in Inner-Mongolia. As for South China except for some parts of coast regions, precipitation is projected to decrease by approximately 5%. The results suggest the substantial difference in regional climatic responses to the GMT rise over China. In general, Northern China has a tendency towards wetness and South China has a trend towards dryness under the background of global warming.

3.2. Individual and joint extreme risks under 2 °C global warming

Figure 2 exhibits the occurrence changes in individual extreme events of abnormal runoff or soil moisture conditions with 2 °C GMT increase. Figure 2(a) indicates that Northern and Northwestern China is dominated by an increasing HR (higher than 90% quantile runoff) with the increase up to 100%, whilst most of the rest parts in China is characterized by a decreasing HR with the reduction ranging from –10 to –60%. It can be observed from Figure 2(b) that China is mainly dominated by an increasing LR (lower than 10% quantile runoff), particularly for the Northwest China in which the LR in most of areas increase by nearly 800%. Large spatial transitions of percentage changes in LR events are found, mainly due to the fact that the historical climatology values is small (Figure S1b, Supporting Information) and the changes are expressed in relative term. Regarding HS (higher than 90% quantile soil moisture) and LS (lower than 10% quantile soil moisture) events shown in Figure 2(c) and (d),

Figure 1. Changes in (a) temperature (°C), precipitation (%) in China under 2 °C global warming.

Figure 2. Changes (%) in occurrences of individual hydrological extremes under 2 °C global warming.

respectively, their variations in Northern China are more complicated than those in Southern China. Overall, Northern China is primarily dominated by increasing HS and LS, whereas Southern China is mainly characterized by negligible changes in HS and increasing LS. On the whole, Northern China is generally dominated by increasing HR, LR, HS, and LS, while South China is generally characterized by decreasing HR and negligible changes in HS and increasing LR and LS, implying that Northern China has a tendency towards wetness and South China has a trend towards dryness, which is consistent with the finding from the climatic perspective as obtained in Figure 1(b).

Global warming would, in most cases, lead to potential increase of extremes of single variable as shown in Figure 2. It should be noted that the timing of the single variable extremes would also change with global warming. Hence, with regard to the concurrent extremes, the

picture would be more complex. It is found that the land areas experiencing joint extreme are much more concentrated (Figure S2). This is due to the fact that joint extremes are representing the concurrence of multiple extremes and the probability of joint extremes should be smaller than the smallest among the multiply extremes. Figure 3 presents the changes in occurrences of joint extremes over China with 2 °C global warming. It is seen from Figure 3(a) that the HRHS (concurrent HR and soil moisture) events will be reduced by 60–100% in much of northwestern and parts of Northeastern China. The changes in the occurrence of joint extreme can be explained mathematically from the nature of the index [see the Equations (5) and (6)]. That is, changes in the frequency and/or timing of single extreme can lead to the changes in the joint extreme. Hence, given the increase of single extreme (Figure 2), the projected decrease of joint extreme are mainly due to

Figure 3. Changes (%) in occurrences of joint hydrological extremes under 2 °C global warming. Note that the white colours indicate the grids with no joint extreme in the reference period.

the altered timing of single extreme with global warming. Increases up to 300% are projected in North China Plain and Inner-Mongolia while no evident changes are found over South China except for small part of Southwest China. The occurrence of LRLS events (Figure 3(b)) representing the concurrent low runoff and low soil moisture conditions will increase greatly in most of the country especially in northwest and south China. Compared with the results based on individual extreme analysis (Figure 2), the magnitude of percentage occurrence changes in joint extremes is much larger in Northwest and South China. For example, more than 1000% increase of joint extreme are projected in part of southern and northern China while the largest increase of single extreme ranges from 600 to 800% in part of western China. Our results suggest that traditional individual risk assessment methods based on either runoff or soil moisture condition may substantially underestimate the risk of extreme events because of ignoring the effects of relationships between the variables. Therefore, we argue that a multivariate viewpoint can provide information which cannot be revealed by individual extreme analysis and is necessary for assessing extreme events risks in a warming climate.

3.3. Response of joint extremes to different levels of global warming

In addition to the changes under 2 °C global warming, the projected changes in joint extremes with 1 and 3 °C global warming were also calculated as shown in Figures

S3 and S4, respectively. Generally, the spatial structure of joint extremes is found to be insensitive to global warming but with the mixed responses at the regional scale in terms of the magnitude of changes. More specifically, land areas experiencing various magnitude levels of changes of HRHS events are projected to decrease with increase of GMT (Figure 4(a)). However, there are some exceptions. For example, land areas experiencing the largest changes (i.e. -100 to -60% and >1000%) of HRHS events will become larger with increase of GMT. For the LRLS events presented in Figure 4(b), areas experiencing decrease of occurrences are constant with increase of GMT while the areas experiencing increase of occurrences are projected to increase linearly with GMT rise. Especially, the land areas experiencing increase more than 1000% of LRLS events will double with Δ GMT up to 3 °C. These areas are generally located in the presently dry regions in northwestern and southwestern China, which is more vulnerable than eastern regions of China to climate change due to its relatively fragile economical–environmental nature. Although large inter-model spread exist, the results imply nonlinear changes of impacts along with Δ GMT with regional disparities in influence magnitudes.

3.4. Sensitivity to the thresholds for extreme definition

Given the fuzzy nature of extreme events, there is no universally accepted definition of extreme event. Therefore, it is of significance to use various levels of threshold to explore the sensitivity of results to the extreme definitions. Similar patterns of changes in joint extremes are found when the alternative 70/30% and 80/20% quantile were used as the extreme thresholds (figures not shown for brevity). Figure 5 shows the land areas experiencing different levels of changes in extreme events using different quantile thresholds under 2 °C global warming. In general, land areas experiencing various levels of changes in the two combinations of extreme events will become larger if adopting lower threshold although the inter-model spread is large. That is, more land areas will experience changes in extreme events using the lower standards for investigating extremes. However, land areas experiencing the highest levels of changes (e.g. 600–1000% and >1000%) will decrease with lower standards. Our results suggest that the threshold definition of extremes could have a large impact on the detection of extreme events, leading to misrepresentation of extreme event changes in a warming climate.

3.5. The effects of changing hydrological regime

With climate warming, the dry/wet conditions in the present would be normal in the future. Using the fixed threshold based on the reference periods would, therefore, leads to misrepresentation of extreme events if not considering the hydrological regime shift. Figure 6 shows the changes in occurrences of the joint extremes using the updated thresholds, which take into account the gradual change of hydrological regime. In this approach, the threshold is derived from the monthly values of the previous 30-year period instead of the fixed historic period

Figure 4. Changes in land areas experiencing different levels of change to global warming up to 3 °C. The box edges illustrate the 25th and 75th percentile, the central mark is the median and the whiskers mark the 5th and 95th percentiles.

(1971–2000). The areas experiencing changes are generally in agreement with that using the traditional fixed thresholds. However, in some regions, the change direction differs between the two methods. Importantly, changes in joint extreme risks were projected to be several times smaller than that using the traditional fixed threshold approach, indicating that an alternative extreme identification that considers adaptation to an altered hydrological regime did have a substantial influence on the projection of future extremes. This additional source of uncertainty associated with impact assessments has great implications for informing policy-makers in designing mitigation and adaption strategies to cope with climate warming. Our results suggest that the approach considering the gradual changes in hydrological regime should be applied in extreme event evaluation in order to cover the full potential impacts, thereby providing more reliable interpretation of future changes in extreme risks.

4. Conclusion and discussions

With global warming, increased temperatures and changes in precipitation will result in fundamental changes in

the distribution of hydrological components in China, with potential changes in the hydrological extremes posing a grand challenge for water resources management. Moreover, climate change impacts are characterized with multiple dimensions. That is, impacts can occur across many dimensions of the hydrology, ecology, social- economy and etc. Hence, it is important to investigate the multi-dimensional impacts in a consistent way. Previous studies mainly used various univariate indicators representing different aspects of impacts (Arnell *et al.*, 2014; Piontek *et al.*, 2014) or using multi-variable based index by merging various source of information into one integrated index (e.g. PDSI, SPEI). However, changes in the concurrent (joint) extremes, which could provide new insights on the impacts, is rarely investigated in a consistent way. Here, we examined the potential changes in the occurrences of joint hydrological extremes of the land surface water components, i.e. concurrent abnormal runoff and soil moisture conditions. Hydrologic time series are derived by driving the calibrated VIC model with bias-corrected climate model outputs. The results are presented as a function of GMT change in order to evaluate the possible policy recommendations and achievable level of GMT increase.

Figure 5. Sensitivity of land areas experiencing different levels of change to the definition of threshold under 2°C global warming. The box edges illustrate the 25th and 75th percentile, the central mark is the median and the whiskers mark the 5th and 95th percentiles.

Our results show substantial changes in joint extremes over China with 2°C global warming. Specifically, results show large increase of occurrence of HRHS in North-east China, LRLS in Northwest and South of China under 2°C global warming. Moreover, the land areas experiencing the largest changes, i.e. the hotspot of climate change impacts over China, are those presently dry/wet regions in general. Notably, the magnitude of percentage occurrence changes in joint extremes is much larger in regions hit by increase of individual extremes and the land areas experiencing changes are also much more concentrated, thereby providing additional information which cannot be revealed by individual extreme analysis. It should be noted that correlations between HR and HS, and LR and LS would exist as governed by the physical hydrological process. The relationship should be similar to that between temperature and precipitation. Because of heterogeneity of land surface characteristics and complex hydrological process, time lags would occur in the occurrence of runoff extreme and soil moisture extreme. When the single extremes overlapped (i.e. concurrence of

hydrological extremes) in certain spatial-temporal scale, more devastating impacts would be caused to the humans and natural systems. With GMT rise up to 3°C, the spatial patterns of changes in the two combinations of joint extremes remain relatively stable. However, changes in land areas experiencing various levels of magnitude of changes exhibited nonlinear relationships with GMT rise. It should be noted that the VIC model did not account for the effects of CO₂ concentration change, which may affect the water resource through vegetation dynamics. Land use and land cover change are also ignored. Hence, the results based on the off-line simulations should mainly represent the effects of climatic change with global warming although land use/cover change impacts were considered in CMIP5 climate outputs (Kumar *et al.*, 2013a, 2013b).

To better inform policy maker, it is always imperative to present the uncertainties in the assessments of climate change impacts. Previous studies have shown that GCM is the largest source of uncertainty (Kay *et al.*, 2009) followed by the emission scenarios (Maurer, 2007). Other studies argue that downscaling may have comparable

Figure 6. Changes (%) in occurrences of joint hydrological extremes based on the transient threshold method under 2°C global warming. Note that the white colours indicate the grids with no joint extreme in the reference period.

effects with that by GCMs (Wilby *et al.*, 2000; Maurun *et al.*, 2010; Chen *et al.*, 2011; Teutschbein and Seibert, 2012). Recently, the uncertainties arising from impact models were shown to be comparable and even larger than GCMs (Haddeland *et al.*, 2014; Pointek *et al.*, 2014; Prudhomme *et al.*, 2014). Nevertheless, to include all aspects of uncertainties is not feasible because no efficient way exist to handle all of them. In this article, the climate projections are bias corrected against observations (Hempel *et al.*, 2013), and the value of them has also been well demonstrated in a number of recent studies (e.g. Dankers *et al.*, 2014; Elliott *et al.*, 2014; Haddeland *et al.*, 2014; Leng and Tang, 2014; Piontek *et al.*, 2014; Prudhomme *et al.*, 2014; Schewe *et al.*, 2014). Moreover, the impact model (i.e. VIC) used in this study was calibrated and validated for the ten river basins over China and was shown to match well with the observed streamflow and soil moisture (Zhang *et al.*, 2014a, 2014b). Instead of dealing with uncertainties as discussed above, we have explored other issues in extreme risk analysis, i.e. uncertainties from the threshold level for extreme definition and the effects of changing hydrological regime.

Our results show that assessments of extreme event risks are indeed depending on the threshold of extreme definition. Compared to the results based on the 90/10% quantile, land areas experiencing extreme risk changes are

found to become larger when using 70/30% and 80/20% quantiles as the thresholds. However, the spatial patterns of changes are relatively insensitive to the various levels of threshold for extreme definitions. Using the fixed threshold derived from the climatology in the historical period, the information on extreme change is apparently useful in guiding the society to mitigate the negative impacts of climate change. On the other hand, it is possible that the extremes would become normal in the future and humans and natural systems may gradually adapt to the changing regimes. Hence, compared to fixed threshold, a transient threshold for a moving reference period can provide new insights and, importantly, might be more appropriate for disaster mitigation because it reflects changes in the hydrological regime over time. Using a transient threshold assuming adaptation to long-term changes in the hydrological regime, Vidal *et al.* (2012) explored the use of a changing drought index for future drought in France. The areas in drought were found to be much smaller when using this transient approach compared to the traditional stationary approach. Van Huijgevoort *et al.* (2014) reported that stationary approach could lead to the misrepresentation of drought events and have a significant impact on the detection of drought events. By comparing the results in Figure 3, increase of joint extreme events is projected to be several time smaller as shown in Figure 6, thus providing lower bounds of possible future changes. This implies that the effects of extremes defined from the fixed historical reference may not exert the same level of impacts on the humans and natural systems in the future. In other words, the impacts of future extremes should fall somewhere between the projections in Figures 3 and 8. This has great implications for the extreme risk analysis because most previous studies used the threshold derived from the fixed historical period. Therefore, we highlight the importance of considering the changing hydrological regime in addition to choosing various levels of threshold for extreme definition, in order to cover the full range of possible changes in extreme risks in a changing climate.

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Supporting Information

The following supporting information is available as part of the online article:

Figure S1. The thresholds of (a) HR, (b) LR, (c) HS and (d) LS derived from the historical period 1971–2000.

Figure S2. The total number of joint extremes in the historical period 1971–2000. Note that the white colours

indicate the grids with no joint extreme in the reference period.

Figure S3. Changes in (a) temperature (°C), precipitation (%) in China under 1 °C global warming.

Figure S4. Changes in (a) temperature (°C), precipitation (%) in China under 3 °C global warming.

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