

A method to study the impact of climate change on variability of river flow: an example from the Guadalupe River in Texas

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Abstract This work introduced a method to study river flow variability in response to climate change by using remote sensing precipitation data, downscaled climate model outputs with bias corrections, and a land surface model. A meteorological forcing dataset representing future climate was constructed via the delta change method in which the modeled change was added to the present-day conditions. The delta change was conducted at a fine spatial and temporal scale to contain the signals of weather events, which exhibit substantial responses to climate change. An empirical transformation technique was further applied to the constructed forcing to ensure a realistic range. The meteorological forcing was then used to drive the land surface model to simulate the future river flow. The results show that preserving fine-scale processes in response to climate change is a necessity to assess climatic impacts on the variability of river flow events.

1 Introduction

There is a broad consensus among global climate models that southwestern North America will become increasingly drier in the 21st century (Seager et al. 2007). One of the most significant impacts of such changes may be on hydrological processes and, particularly, river flow regimes. Extreme events, which are typically small scale processes, are likely to respond substantially to anthropogenically enhanced greenhouse forcing (Meehl et al. 2009). At present, such events affect a wide variety of natural and human systems, and future changes in their frequency could have dramatic ecological, economic, and sociological consequences.

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Many previous climate change impact studies have focused on assessing the potential implication of global warming for water resources at a national or regional level (e.g. Arnell et al. 1997). Despite their undeniable importance for long-term planning, changes in annual or monthly runoff may give very little information on the changes in the extreme river flow events. Assessing annual runoff can be done using simple monthly models. However, continuous runoff modeling for river flow regime assessment requires input at sub-daily time-step to resolve the extreme events (Prudhomme and Reynard 2002). Moreover, the spatial scales of global climate models (GCMs) outputs are not sufficient for hydrological simulations at sub-daily scales.

Dynamical downscaling, which downscales the output of GCMs by using Regional Climate Models (RCMs), provides a way to overcome the drawbacks of GCMs. However, model bias remains a critical problem (Cubasch et al. 1996; Mearns et al. 1999). The quality of the absolute estimates of climate models calls into question the direct use of the outputs for hydrological modeling. The delta change approach is a common transfer method used to date for bias removal (e.g., Gleick 1986; Arnell 1996; Gellens and Roulin 1998; Lettenmaier et al. 1999; Middelkoop et al. 2001; Bergström et al. 2003; Graham 2004). The changes predicted by the climate models are more favored than the absolute values due to the bias cancellation (Smith and Pitts 1997). The present conditions are then altered according to the modeled changes. The delta-perturbed database is thereafter used to make offline simulations with a hydrological model to provide a response to the future climate. To reduce the noise, the model outputs were usually filtered or averaged over larger regions and a longer period in deriving the delta changes (Andréasson et al. 2004; Graham et al. 2007a, b). A major drawback of this manipulation is that the representation of extremes, especially for precipitation, from future climate scenarios was effectively filtered out in the transfer process. Consequently, the extremes were simply the extremes from present climate observations that have either been slightly enhanced or dampened according to the delta factors. However, it is the extreme events that often cause significant impacts on human society.

This paper reports a method to project the change in short-term river flow events. We chose a climate change scenario with a typically moderate change in precipitation and a four-year period of observations for our exploration. Here we want to emphasize that this choice is for illustrating our methodology rather than seeking comprehensive hydrological predictions, since these predictions would require multi-model and multi-scenario projections as well as a longer analyzing period.

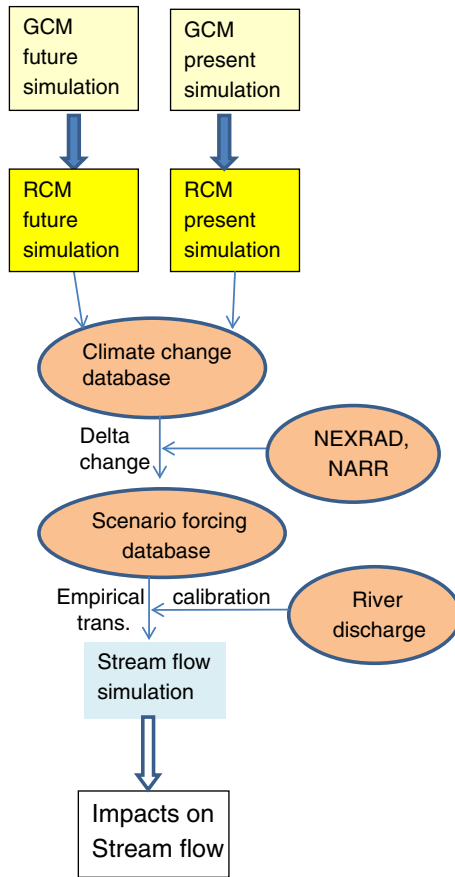
Although our method is performed on one scenario, it should apply to different climate projections. Since the extremes are short-term events, the essential part of the methodology focuses on the skills to preserve the response of short term, fine-scale processes to climate change through bias correction processes. The bias correction was performed after the dynamic downscaling.

This paper provides the first study on the impacts of climate change on river flow in south-central Texas at a sub-daily time scale. The data and methodology are described in Section 2; the runoff calibration and future climate projections are presented in Section 3; the conclusions and discussion are given in Section 4.

2 Data and methodology

Figure 1 is a schematic diagram showing how regional climate model outputs were obtained, bias-corrected, before their use to drive a land surface model (LSM) for river flow simulations. A future meteorological forcing was constructed by using the delta change

Fig. 1 The analysis chain for assessing the climatic impacts on the river flow

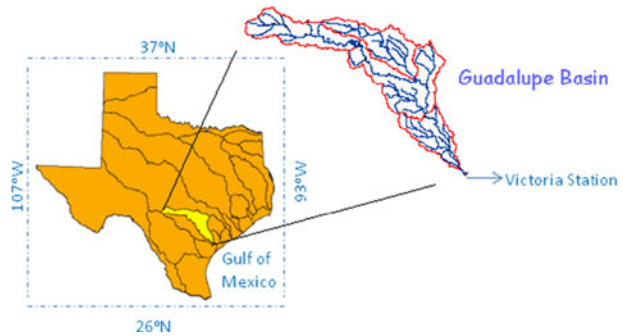


method and an empirical transformation technique. The meteorological forcing was then used to drive an LSM to simulate the future river flow. The LSM derives river flow through water-balance within the river basin (Lohmann et al. 1998). The LSM does not take into account the municipal, industrial and agriculture withdrawals, which might contribute to uncertainty in the river simulation. The projected streamflow was estimated from total runoff for the whole basin based on the assumption that the net water outflow is nearly zero everywhere except at the basin outlet (i.e. river mouth). Below is a further description of the models, data and methodology that were used in this work.

2.1 The Noah land surface model and NEXRAD precipitation

The Noah LSM version 2.2 (Ek et al. 2003) was used to simulate runoff over the Guadalupe River Basin, which has an area of 3,256 km² and runs from Kerr County, Texas to San Antonio Bay on the Gulf of Mexico as shown in Fig. 2. The Noah LSM is a state of the art land surface scheme, which dynamically predicts soil temperature, soil water/ice, canopy water, snow cover and surface and subsurface runoff. The Noah LSM is governed by mass conservation and a diffusive form of the Richard's equation (Rosero et al. 2011). In the Noah LSM, the predicted state variables are calculated by simultaneously solving energy and water balance equations for a one dimensional soil-snow-vegetation column. The Noah LSM used in

Fig. 2 Map showing area of the Guadalupe Basin and location of Victoria Station in Texas. The blue lines in the Guadalupe Basin indicates Guadalupe River flow network



this paper was driven by seven meteorological forcing variables (precipitation, air temperature, humidity, wind speed, surface pressure, and incoming short and longwave radiation components), with a spatial interval of 0.9 km and a temporal interval of 3 h. All the variables except precipitation were extracted from the North American Regional Reanalysis (NARR) (Mesinger et al. 2006). NARR is a three-hourly, 32-km reanalysis dataset available from 1979 to present, and is arguably the best long-term dynamical reanalysis dataset for the continental United States (CONUS), but the uncertainty may still exist (e.g., Berg et al. 2003). A linear interpolation was applied to convert 32-km forcing data to 0.9 km Noah LSM grid. The river flow simulation was calibrated using the U.S. Geological Survey daily discharge observations at Victoria station, which is located at the mouth of the Guadalupe River (see Fig. 2).

Precipitation is the key for river flow modeling, so having a high-quality precipitation dataset is crucial. The precipitation data used in this study came from the national NEXRAD (Weather Surveillance Radar-1988 Doppler) remote sensing database. The National Weather Service (NWS) NEXRAD has revolutionized the NWS forecast and warning programs through improved detection of severe wind, precipitation, hail, and tornadoes (Krajewski and Smith 2002). Efforts for validation of the NEXRAD Stage III precipitation have been carried out in many regions and different climate regimes (Smith et al. 1996; Young et al. 2000; Jayakrishnan et al. 2004; Xie et al. 2006). A recent study in the San Antonio/Guadalupe River basin using 50 high-quality rain gauges to validate the NEXRAD MPE (Stage III) precipitation of 2004, observed a correlation coefficient (r) of 0.80 for the entire year and 0.96 for the NEXRAD grid cell area where spatially uniform precipitation events occurred (Wang et al. 2008). In this study, a physically-based parsimonious multivariate-regression algorithm (see Appendix) was used to interpolate the hourly 4-km NEXRAD precipitation between 2004 and 2007 to hourly 0.9 km to drive the Noah LSM. The NEXRAD precipitation over the Guadalupe River Basin is shown in Fig. 3. The NEXRAD precipitation can well record the rainfall events that occurred in this region (Wang et al. 2008). Together with the daily river flow observation from USGS and the NARR data, they construct high quality datasets used for the river flow calibration.

2.2 Future climate simulation and bias correction

2.2.1 Dynamical downscaling

Jiang et al. (2008) described the method that produced the climate model outputs used in this study. Present and future regional climate fields were obtained by dynamically downscaling the NCAR Community Climate System Model version 3 (CCSM3) (Collins et al. 2006) outputs to the regional scale. The horizontal scale of CCSM3 is T85 (~1.41°). The

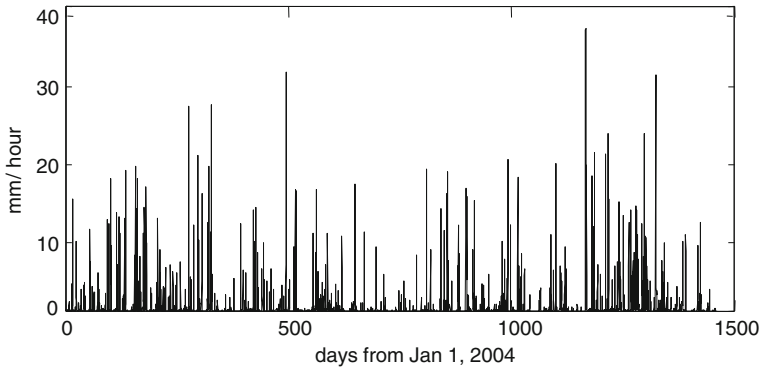


Fig. 3 NEXRAD 3-h mean precipitation rate averaged over Guadalupe Basin in Texas between 2004 and 2007. Note the change of 4-year accumulated precipitation after 50 years was shown in lower panel in Fig. 7

greenhouse gas concentrations during the CCSM3 simulation period used in this study follow the IPCC Special Report on Emission Scenarios (SRES) A1B. The A1B scenario is a mid-line scenario for carbon dioxide output and economic growth; the predicted carbon dioxide emissions increase until around 2050. The downscaling was achieved by running the Weather Research and Forecasting (WRF) Model with Advanced Research dynamic core version 2.2 (Skamarock et al. 2005) at fine-scales of 18 km. The WRF receives its lateral boundary conditions from a one-way link with climate variables that have already been outputted by the CCSM3. The WRF is a next-generation, limited-area, non-hydrostatic, with terrain following eta-coordinate mesoscale modeling system designed to serve both operational forecasting and atmospheric research needs. The model output was saved every 3 h, which was used as the input of the Noah LSM for the study of impact of the climate change on the river flow. Note a linear interpolation was also performed to convert 18-km forcing data to the Noah LSM model grid. Even if dynamical downscaling improves the realism of simulated regional climate properties, some important biases still exist in the model outputs, especially concerning precipitation. To simulate realistically the regional hydrology after dynamical downscaling, raw RCM model results have thus to be bias-corrected.

2.2.2 Bias corrections

The delta change approach was adopted in this paper to construct future climate forcing. In this approach, the future and present downscaled outputs were used to derive the delta change of future climate with respect to the present-day climate. To avoid losing signals of short-term weather events, we applied the delta change approach at each 3-h time step on each Noah LSM model grid cell. The advantage of performing the delta change at fine-scales is that it can preserve the extreme weather events that occur on these scales to the fullest extent possible and therefore, it contained the signals of weather events, which were mostly filtered out in previous studies (see also the discussion in Introduction). This fine-scale construction is very computationally intensive. Considering the existing computing resource and the availability of NEXRAD precipitation, we chose a 4-year period for our experiment, which is long enough to observe the substantial change of weather events in response to climatic change. Also, this step by step construction can generate certain unrealistic values in the forcing, for example, negative precipitation. To

deal with this problem, an empirical transformation technique, i.e., 'quantile-based' bias correction (which was discussed later in detail), was further applied to the constructed forcing to ensure a realistic range. The 'quantile-based' technique does not alter the relativity of the values (Boe et al. 2007) and largely remains the original signal of climate change.

Before the delta change was extracted, the total modeled 4-year present precipitation was scaled to match NEXRAD observation at each grid cell. The future precipitation at each grid cell was adjusted by the same scaling factor correspondingly. This procedure is to render the modeled precipitation to more realistic values. In the delta change approach, the pre-corrected scenario time series $V_{p_{scen}}(t+50Y)$ are given by:

$$V_{p_{scen}}(t+50Y) = V_{obs}(t) + (V_{fut}(t+50Y) - V_{pres}(t)) \quad (1)$$

where V_{obs} denotes the observation (i.e., NEXRAD), V_{fut} denotes the modeled future climate simulations, and V_{pres} denotes the modeled present climate simulations. $(t+50Y)$ denotes the time after a 50-year shift (which was admittedly arbitrary). Supposing the model can realistically simulate the future climate, it would be able to realistically simulate scenario time series according to Eq. (1). In reality, the delta change (the second term on the right side) still have errors, especially concerning precipitation. To improve the realism of the downscaled climate properties, a "quantile based" bias correction technique (Deque 2007; Reichle and Koster 2004; Wood et al. 2004) was used to translate $V_{p_{scen}}$ to a plausible range and distribution density with respect to observations to improve the realism of simulated regional climate properties. The 'quantile-based' correction would place further constraints on the correction of the future scenario. Negative values of $V_{p_{scen}}$ are possible during initial calculations. An anomaly (which is relative to the long time mean) was used to allow for negative values in the quantile-quantile transformation. The time mean was then added back after the transformation to ensure that there is no negative value in $V_{p_{scen}}$. Therefore, in our application, the 'quantile-based' correction was also used to correct the negative values. More details are described below.

For a forcing variable, the Cumulative Density Function (CDF) of the anomaly was generated at each grid cell from NEXRAD data (for precipitation) or NARR reanalysis. This CDF was used to remove the bias for the corresponding anomaly of $V_{p_{scen}}$ at the same grid cell as described in Fig. 4. For the anomaly value $V'_{p_{scen}}(t+50Y)$ of the variable x at the time $(t+50Y)$ in the pre-corrected climate scenario, the corresponding CDF $P_{p_{scen}}$ is found on the $CDF_{p_{scen}}$ (which is the CDF of the pre-corrected scenario simulation). Then, the value $V'_{scen}(t+50Y)$ of x such as $P_o = P_{p_{scen}}$ is searched on the CDF_{obs} (which is the CDF of the observations). This value (i.e. $V'_{scen}(t+50Y)$) is finally used as the corrected anomaly value in the climate scenario. Finally, the time mean of the observation was added back to $V'_{scen}(t+50Y)$ to produce the final scenario forcing value $V_{scen}(t+50Y)$. A few values in the climate scenario may exceed the greatest value found in the observations. In these cases, we preserved the values without change.

3 Results and discussion

3.1 Stream flow validation

The river flow was simulated using the Noah LSM driven by NEXRAD precipitation and NARR meteorological forcing. Figure 5 shows daily averaged Guadalupe river flow and

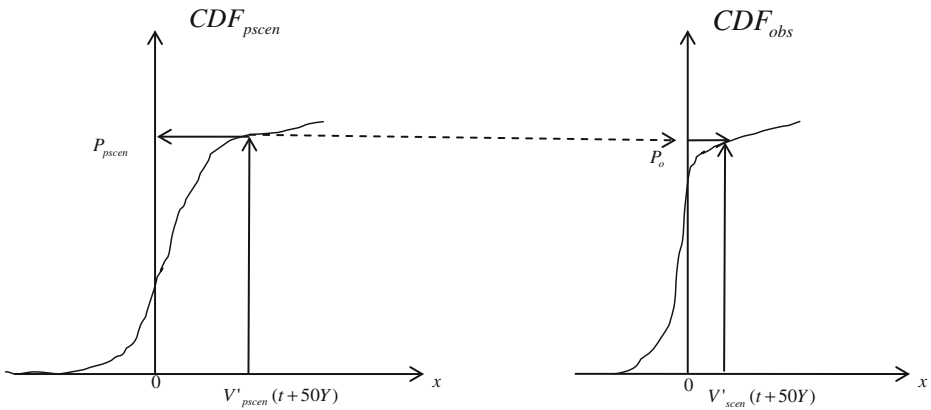


Fig. 4 Principle scheme of bias correction using quantile–quantile mapping technique. $V'_{pscen}(t+50Y)$ is the anomaly value of the variable x at the time $(t+50Y)$ in the pre-corrected climate scenario. CDF_{pscen} is the CDF of the pre-corrected scenario simulation. CDF_{obs} is the CDF of the observations. $V'_{scen}(t+50Y)$ is the corrected anomaly value in the climate scenario. See more discussion in the text body

observed river flow at Victoria station (the first two months was used as spin-up period and not shown in the Fig. 5). The observed river flow exhibits various typical large and small peaks (events) and low flow periods, offering a good opportunity to test the performance of the simulation. The general quality of river flow simulation lies in how well the model captures the river flow events as well as the timing to capture the events. It can be seen from Fig. 5 that the model is able to capture most of the large river flow events with little delay. For example, the large river flow event around the 200th day was nicely modeled in terms of the strength, duration and timing. The correlation between the simulated and observed river flow is 0.83. The model simulates the high-flow variability better than the low-flow variability. The simulation of the low-flow variability is more challenging for all models due to its relative small variability. However, we are more interested in extreme

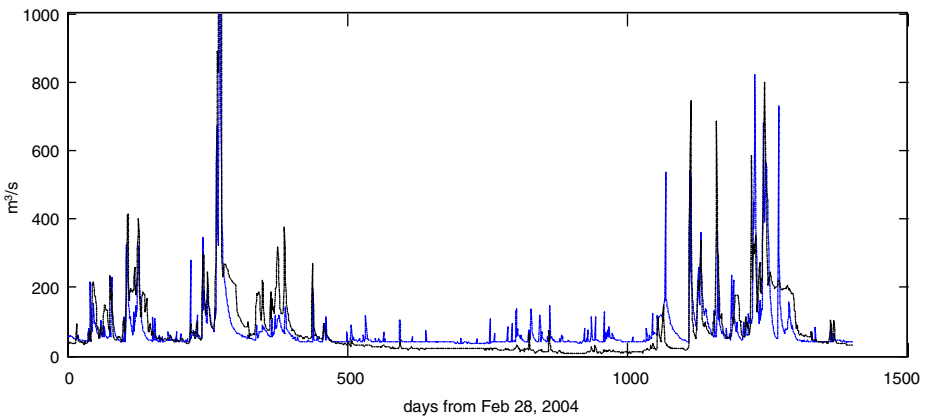


Fig. 5 Daily mean Guadalupe River flows from observation (black line) and simulation (blue line). The correlation between observational and projected flows is 0.83. The modeled Nash–Sutcliffe efficiency coefficient is 0.71

events (which are short-term large amplitudes of river flow events) since they have more significant influence on society. The Nash–Sutcliffe Efficiency (NSE) was calculated for this period. The NSE is generally used to assess the predictive power of a model. It is defined as:

$$E = 1 - \frac{\sum_{t=1}^T (Q_o^t - Q_m^t)^2}{\sum_{t=1}^T (Q_o^t - \bar{Q}_o)^2} \quad (2)$$

where Q_o is observed discharge, and Q_m^t is modeled discharge, Q_o^t is observed discharge at time t . Nash–Sutcliffe efficiencies range from $-\infty$ to 1. The second term in Eq. (2) is the ratio between the variance of observation-model difference and the variance of the observation. This measure is used to describe the predictive accuracy of the model as long as there are observed data to compare with the model results. The closer the model efficiency is to 1, the more accurate the model is. The NSE of the simulation is 0.71. Essentially, it represents the proportion of variability in a dataset that is accounted for by the model (i.e., the coefficient of determination R^2). The resulted NSE suggests that the model captured the most variability of the observed river flow. Note the LSM relates to the rainfall to river flow via water-balance within the river basin, which allows for losses along the river path. Yet there are mismatches in some small river flow events. The model does not consider the base flow variability and municipal and agriculture withdrawals. There might be more ground water storage or withdrawals during the rain events and more return flows during low flow conditions. These factors can modify the river flow and should be considered in more sophisticated models in operational practice. Note again that the paper is to illustrate our methodology rather than pursue comprehensive predictions. We believe that our approach is suitable for the purpose of this study, considering the relatively good correlation and performance of the model in simulating the river flow events.

3.2 The projected changes

Assessment of impact of climate change on river flow events requires input forcing that has a substantial response to climate change at daily or even hourly step. This is because river flow events are driven by the weather events that occur on these fine-scales. This section gives more attention to precipitation since it is the most critical forcing that affects river flow simulation. Figure 6 shows the 3-h mean projected precipitation over Guadalupe Basin from 2054 to 2057.

It can be seen that the projected precipitation exhibits many short-term events. Here we emphasize again that the application of delta change at fine-scales, i.e., scales at which short- and small-scale weather events occur, is the key for projecting these events. Please note Fig. 6 is not the forecast of future precipitation although future weather events have to be expressed at these scales. However, we do expect the scenario forcing that contains fine-scale processes can carry the information on the trend of the future climate in this region, such as the change of probability and distribution of precipitation. It is shown later in this paper that the response of fine scale processes to climate change is critical for the assessment of the impact of climate change on river flow.

Quantifying the uncertainty of climate change is difficult because of the inaccessibility of the future climate. But it is reasonable to compare the result to other relevant projections. Figure 7 gives the four-year accumulated precipitation and the decrease of the future precipitation. The total precipitation decrease is about 10% of the NEXRAD precipitation.

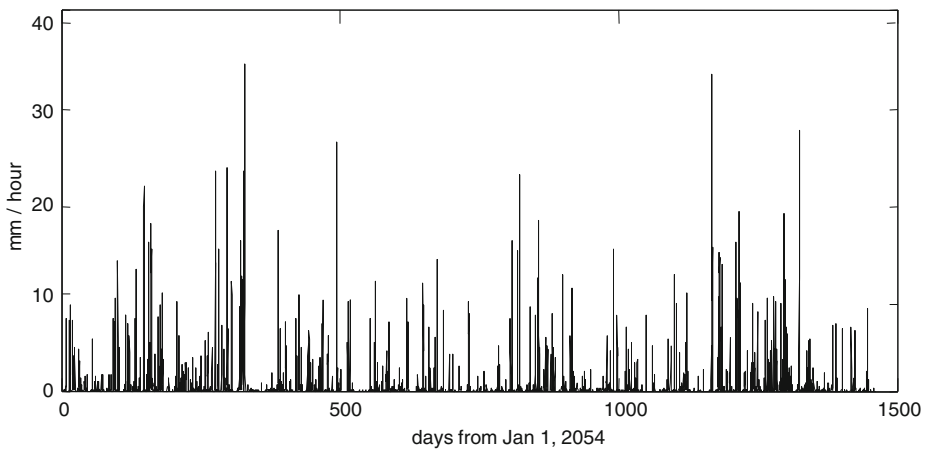


Fig. 6 Projected 3-h mean precipitation rate averaged over Guadalupe Basin in Texas between 2054 and 2057

This result is agreeable with the prediction from 19 climate models under the same scenario that southwestern North America (which includes the Guadalupe Basin) is in an imminent transition to a more arid climate (Seager et al. 2007). The precipitation decrease has a moderate range between 0 and 30% of the NEXRAD precipitation. The pattern of precipitation change exhibits an interesting geographic variation. The most apparent feature of the four-year accumulated NEXRAD precipitation is the strongest precipitation at the southeastern Guadalupe Basin, which is about twice of the other regions due to the adjacency to the Gulf of Mexico. Correspondingly, the largest projected decrease of precipitation also occurs at the southeastern Guadalupe Basin. The NEXRAD precipitation is not dynamically constrained by any climate models. The sensible agreement in the accumulation patterns between precipitation change and the NEXRAD observation implies the soundness of the projection.

Figure 8 shows the annual cycle of 2-m air temperature. The temperature of the Guadalupe Basin has a moderate increase in the next 50 years. The change of temperature peaks around 200th day (which is about 2.5°C degree), decreases gradually, and is stable at about 1.7°C degree after 270th day. This indicates a relatively larger temperature increase in the first 6 months. It can be seen that the temperature apparently has a more regular change than that of precipitation. The relationship between precipitation changes and temperature changes is not clear. If we pick 2.0°C as a temperature threshold value, it suggests a decrease in precipitation when the temperature increase is above 2.0°C, and a corresponding increase in precipitation when the temperature below is below 2.0°C. Actually, many climate model predictions suggest the existence of similar temperature threshold values (e.g. 2.5°C) for the 21st century.

3.3 Impacts on the river flow

Assessing climate change impacts on river flow events relies on the scenario forcing that resolves short-scale weather events, which was achieved by preserving the fine-scale processes in the climate change. Figure 9 shows the present and projected Guadalupe river flow (the first 2 months was used as spin-up period and not shown in Fig. 9). River flow events are essentially the responses to weather events in certain complex way. It can also be

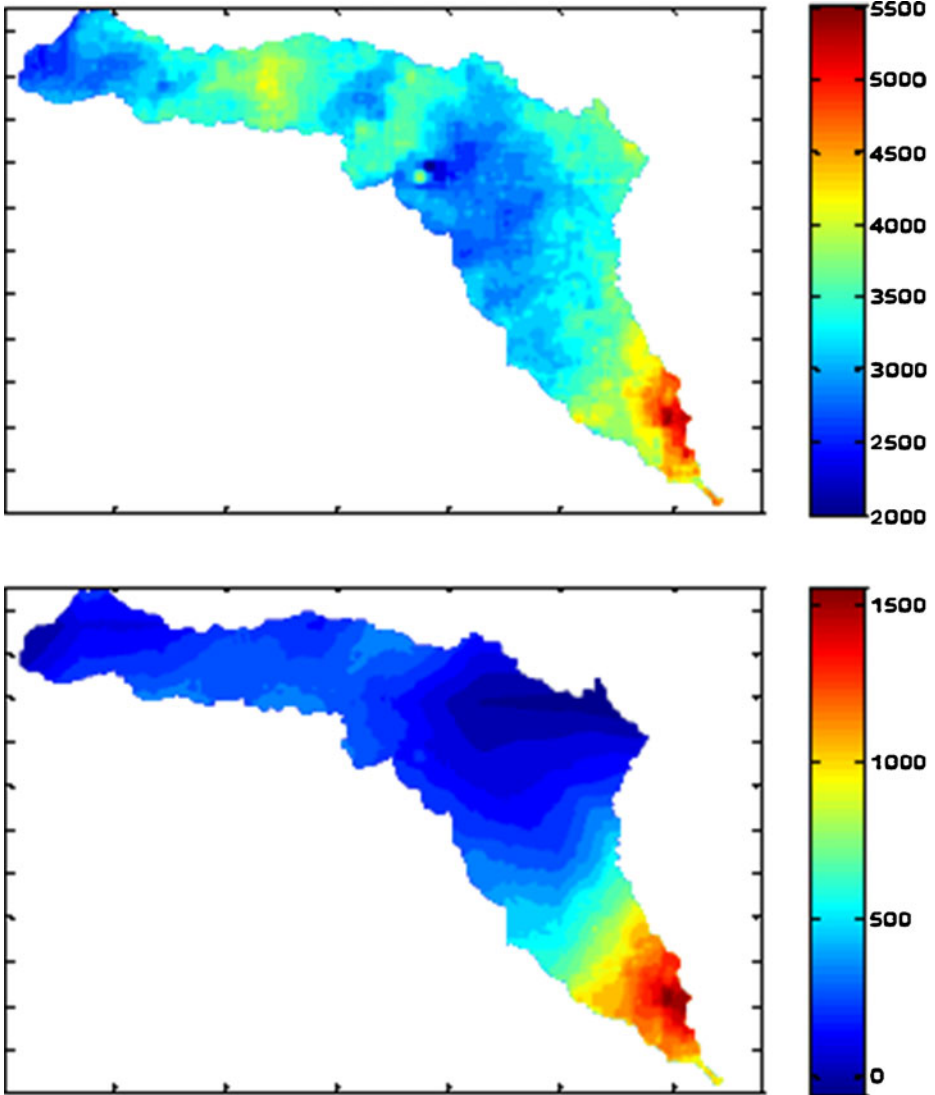
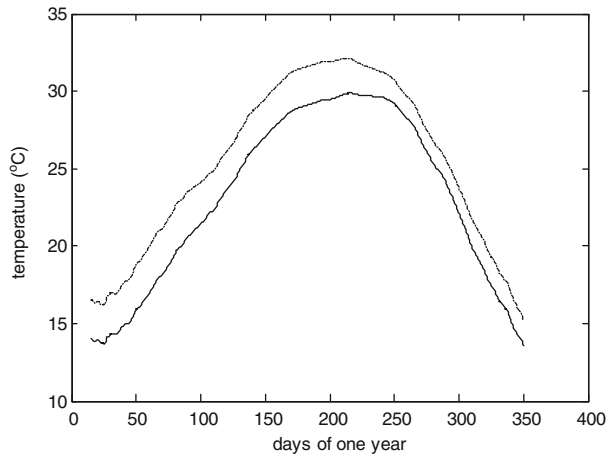


Fig. 7 *Upper panel:* accumulated precipitation in Guadalupe Basin from NEXRAD for period from 2004 to 2007; *Lower panel:* the decrease of accumulated precipitation in Guadalupe Basin after 50 years. Note the ranges of colour bars are different. Unit: mm

seen that there are substantial new river flow events (peaks) appear in the scenario river flow. Although some present river flow variability was passed into the scenario river flow, most of them are largely altered. Since river events have a time scale as short as 1 day, the scenario river flow containing these short time changes has a tremendous advantage in studying the impact on river flow events.

To quantify the impact of the climate change on river flow, we define three interesting river flow levels: large flow, modest high flow and low flow. The large flow, which can cause harmful flooding, is defined as the flow which has a discharge that is nine times

Fig. 8 The annual temperatures after 30-day moving average for 2004–2007 (solid line) and 2054–2057 (dashed line)



larger than that of the four-year mean flow; the low flow, which represents drought condition, is defined as the flow which has a discharge that is smaller than half of that of the mean flow; the modest high flow, which might cause modest flooding, is defined as the flow which has a discharge that is in the range between three and nine times of that of the mean flow. There is no uniform definition of river flow levels. Although somewhat subjective, we defined the levels according to river flow records and the corresponding flood and drought conditions in this region. The probability of a river flow event is estimated as the ratio of the day amount in that level divided by the total four year days. The change of day amount in a river flow level represents the change of the probability of that river flow event. Figure 10 illustrates how the climate change impacts the river flow. It

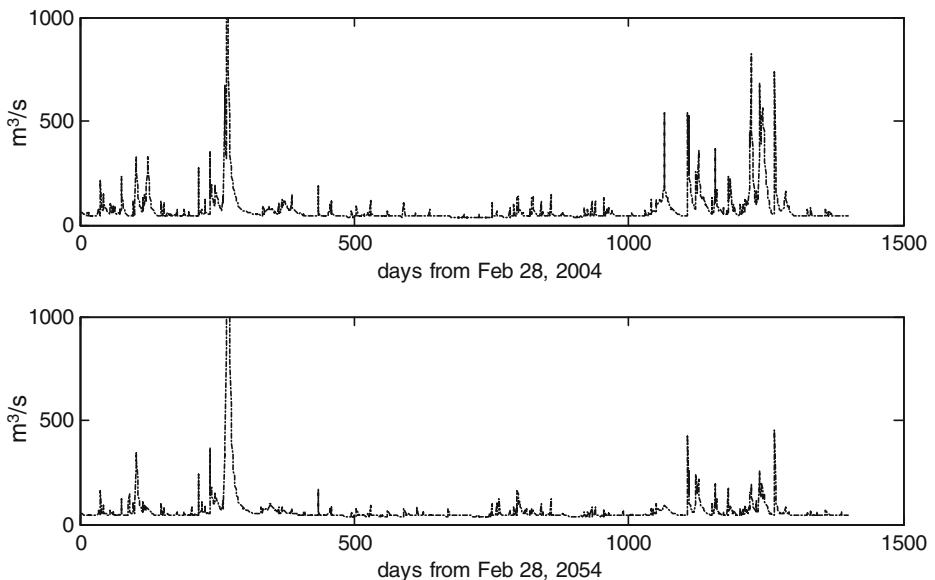
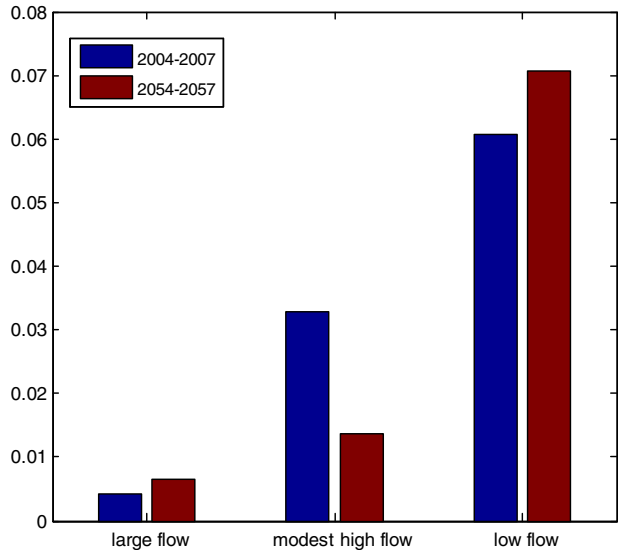


Fig. 9 Daily mean Guadalupe river flows for 2004–2007 (upper panel) and 2054–2057 (lower panel)

Fig. 10 The probabilities of river flow events for the present (2004–2007) and future climates (2054–2057). The definitions for the river flow events are described in the text



shows that the probabilities of harmful large flows increases from 0.4% to 0.6%; the probability of modest high flows decline from 3.3% to 0.7%; the probability of low flow (which indicates the drought condition) increases from 0.6% to 0.7%. Our results show that, in a warmer world, river flow tends to be concentrated into more intense events, with longer periods of low flow in between. The likelihood of the modest large flow actually tends to decline. Please note the uncertainty of the above probability is still unknown. It needs to be cautious when dealing with small probability changes. However, we believe it is a good way to quantify the impacts on the river flow events, considering the annual or monthly river flow would give very little information in the river flow regime, especially extremes.

4 Conclusions and discussion

Obtaining sub-daily weather events in response to climate change is of great challenge for future climate projection, and is critical for studying the hydrological impacts of the climate change. This work introduced a method to retain the signals of weather events in scenario forcing, which made it possible to explore the variability of river flow events in response the change of climate. The delta change approach method was performed at each 3-h time step on each Noah LSM model grid cell to preserve the signals of extreme weather events that occur on these scales. An empirical transformation technique was further applied to the constructed forcing to ensure a realistic range. It was shown that the response of fine scale processes to climate change is critical for the assessment of the impact of climate change on river flow events.

Here we want to emphasize again that the choice of a moderate climate change scenario is for methodological exploration rather than the real prediction. Although the research of individual projections for specific scenarios is important, we think it is also useful to have an effective method to evaluate the impact of any scenario. The method presented in this paper is still tentative. The performance of the method will finally depend on the quality of climate change projections. But one point embodied in this study can be important

reference for future research, i.e., preserving the response of fine-scale processes to climate change is a necessity to assess its impact on the variability of river regime events.

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Appendix

Physically-based parsimonious multivariate-regression algorithm

Physically-based parsimonious multivariate-regression algorithm is an statistical algorithm used to downscale low-resolution spatial precipitation fields (Guan et al. 2009). This algorithm auto-searches precipitation spatial structures (rain-pixel clusters), and orographic effects on precipitation distribution without prior knowledge of atmospheric setting. It is composed of three components: rain-pixel clustering, multivariate regression, and random cascade. The first step is clustering, which separate the rain pixels into different clusters by rain rates and their spatial connections, because the storm structure and the associated physical processes are believed to be more similar within one raining pixel cluster than between clusters. The second step is to examine alternative cluster structures, and find the one having the best agreement between the regression estimates and the original NEXRAD pixel values. For all identified clusters, ASOAdEK regression [Guan et al. 2009, 2005] is applied,

$$P = b_0 + b_1X + b_2Y + b_3XY + b_4X^2 + b_5Y^2 + b_6Z + b_7 \cos \alpha + b_8 \sin \alpha$$

where P is precipitation rate, X is the longitudinal geographic coordinate, Y is the latitudinal coordinate, Z is the elevation, α is the terrain aspect, and the b_i are fitted coefficients. After regression, the sum of precipitation for the small pixels (calculated from the regression function) is compared to the original large pixel value, and their correlation coefficient is calculated for each cluster and assigned to each large pixel and small pixels within the cluster. Guan et al. (2009) demonstrated the good performance of the algorithm for downscaling NEXRAD precipitation at both daily and hourly temporal resolutions for the northern New Mexico mountainous terrain and the central Texas Hill Country.

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