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<td>Qin, Xiaosheng; Lu, Yan</td>
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Study of Climate Change Impact on Flood Frequencies: A Combined Weather Generator and Hydrological Modeling Approach*

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ABSTRACT

Climate change is expected to lead to more frequent and intensive flooding problems for watersheds in the south part of China. This study presented a coupled Long Ashton Research Station Weather Generator (LARS-WG) and Semidistributed Land Use–Based Runoff Processes (SLURP) approach for flood frequency analysis and applied it to the Heshui watershed, China. LARS-WG, as a weather generator, was used to offer 46 sets of climate data from seven general circulation models (GCMs) under various emission scenarios (i.e., A1B, B1, and A2) over near-term and future periods (i.e., $T_1$, 2011–30; $T_2$, 2046–65; and $T_3$, 2080–99). SLURP is a continuous, spatially distributed hydrological model that uses parameters from physiographic data to simulate the hydrological cycle from precipitation to runoff. Flood frequency analysis based on Pearson type III distributions was followed to analyze statistics of annual peaks. The final results (from ensembles of multimodels and multiscenarios) indicated that the magnitudes of a 200-yr return flood for $T_1$, $T_2$, and $T_3$ would increase by 5.23%, 4.08%, and 12.92%, respectively, in comparison to the baseline level; those under the most extreme condition (i.e., worst scenario) would be 25.18%, 31.00%, and 44.46%, respectively. Various GCMs and emission scenarios suggested different results. But the ECHAM5/Max Planck Institute Ocean Model was found to give a more worrying intensification of flood risks and the Commonwealth Scientific and Industrial Research Organisation Mark, version 3.0, and the Community Climate System Model, version 3, were relatively conservative. The study results were useful in helping gain insight into the flood risks and its uncertainty under future climate change conditions for the Heshui watershed, and the proposed methodology is also applicable to many other watersheds in Southeast Asia with similar climatic conditions.

1. Introduction

Floods have resulted in tremendous risks and damages to our society. It is now widely recognized that such events will become more frequent and intensive with the changing climate (Hirabayashi et al. 2013). To predict flood risks for future conditions, scientists have relied heavily on coupled climate and hydrological models.

The climate models are classified to general circulation models (GCMs) and regional climate models (RCMs) crossing over the world. Hydrological models also have a wide variety of types, depending on the nature of algorithms, such as physically based distributed models and black-box models (Okkan and Serbes 2012; Wu et al. 2012; Zhang et al. 2012; Thompson et al. 2013).

The resolutions of GCMs and RCMs are generally coarse for those small-scale watersheds for flood-risk analysis, although they may be useful for medium-sized (e.g., above 10,000 km² of drainage area) or continental river basins. The downscaling methods (mainly categorized into dynamic downscaling and statistical downscaling) could help bridge such a gap. Compared with the dynamic way, statistical downscaling is relatively easy to transfer to different regions and more computationally efficient and could offer the point-scale
climate data from the output of GCMs (Wilby and Wigley 1997). The foundation of statistical downscaling is to build the stochastic or deterministic relationship between the large-scale variables (predictor) and local weather information (predictand; Fowler et al. 2007). It can be classified into three major groups, including regression models (Tripathi et al. 2006; Cannon 2011; Ghosh and Katkar 2012), weather typing schemes (Bellone et al. 2000; Enke et al. 2005), and weather generators (Richardson and Wright 1984; Semenov and Barrow 1997; Hayhoe 2000). Among these types, stochastic weather generator has been considered a flexible and parsimonious tool to generate synthetic climate data, based on the statistical characteristics of local weather stations and/or climate change scenarios from large-scale GCMs. It could be used either alone to reproduce local weather data or combined with other methods, such as a regression model [Statistical Downscaling Model (SDSM); Wilby et al. 2002], to provide more reliable simulation.

The Long Ashton Research Stochastic Weather Generator (LARS-WG) is one of the most widely used tools for climate change impact studies (Semenov and Stratonovitch 2010). Many previous works have focused on the comparison between LARS-WG and other types of downscaling methods, such as Weather Generator (WGEN; Semenov et al. 1998), Agriculture and Agri-Food Canada Weather Generator (AAFC-WG; Qian et al. 2005), and SDSM (Hashmi et al. 2011). LARS-WG showed a good capability in keeping the key statistical properties and has been widely used for modeling weather events around the world, such as in the United Kingdom (Semenov 2008), New Zealand (Hashmi et al. 2009), and Africa (Chen et al. 2012). More recently, LARS-WG has been used to examine climate change impacts on hydrological processes. Zarghami et al. (2011) applied LARS-WG to downscale precipitation and temperature from Hadley Centre Coupled Model, version 3 (HadCM3) A1B, A2, and B1 emission scenarios and combined it with an artificial neural network (ANN) model to simulate the runoff variation under climate change conditions in Iran. Kim et al. (2013) used the LARS-WG and Soil and Water Assessment Tool (SWAT) to assess the bioenergy crops and climate change on hydrometeorology in the Yazoo River basin, Mississippi, United States.

Hydrological models have been extensively used in climate change impact studies as they could effectively help build a linkage between climate data and surface runoff (Amengual et al. 2007). Many physically based hydrological models have been developed and widely used in recent decades, such as the Precipitation–Runoff Modeling System (PRMS; Leavesley et al. 1983), Semi-distributed Land Use–Based Runoff Processes (SLURP; Kite et al. 1994), Hydrologic Simulation Program–Fortran (HSPF; Bicknell et al. 1996), and SWAT (Arnold et al. 1998). SLURP, as a semidistributed hydrological model, has been widely used for studying hydrological processes and climate change impacts at various basin levels, such as the mountainous region of Canada (over 275 000 km²; Thorne and Woo 2006), mountainous watershed of South Korea (about 6661.3 km²; Ha et al. 2010), and the urbanized watershed of South Korea (260.4 km²; Ahn et al. 2011). The related study results indicated that the SLURP model could generate accurate simulations through parameter optimization. Furthermore, successful applications of SLURP were also reported in the Yangtze River basin, China (Long et al. 2008). Wu et al. (2012) also used the SLURP model to assess the impacts of climate and land use changes on the migration of nonpoint source nitrogen and phosphorus in the Jialing River watershed, China (with an area of 156 141 km²). The model showed an average Nash–Sutcliffe coefficient at 0.79 for both calibration and verification periods.

In addition, many other studies were devoted to the field of climate change impact on hydrological processes or flood-risk analysis. Early examples can be referred to Burrel et al. (2007), Kang et al. (2007), and Brekke et al. (2009), among others. In more recent years, Kim et al. (2011) applied a weather generator based on a nonstationary Markov chain model to downscale meteorological data from an RCM in Han River, South Korea. The downscaled data were used as inputs for the SLURP model to assess flood frequency variation under changed climate. The results showed that the runoff would increase for future periods at a maximum rate of 40%. Meenu et al. (2013) applied the statistical downscaling tool, SDSM, and a hydrological model, the Hydrologic Engineering Center’s Hydrologic Modeling System (HEC-HMS) to assess the hydrological responses under climate change conditions in India. The results showed an increasing tendency of rainfall and runoff in the future period. Das and Simonovic (2012) investigated the climate change–related uncertainty in the frequency of flood flows for the upper Thames River basin (Ontario, Canada) using a wide range of climate models (including 15 climate model scenarios from six GCMs). The study indicated the existence of a large uncertainty in all of the projected future design floods. There were also a number of studies in China. Liu et al. (2011) used SDSM to downscale the GCMs’ (HadCM3) data and plugged the results into the SWAT model for assessing the hydrological responses under climate change conditions in the Yellow River basin. The results showed that the annual streamflow would generally increase under different emission scenarios. Liu et al. (2013) used a physically
based distributed hydrological model, Hydrologiska Byråns Vattenbalansavdelning (HVB-D) to investigate the uncertainty in hydrological impacts of climate change based on multiple GCMs in Zhujiang River, south China.

Based on the review of the previous studies, it is indicated that LARS-WG is particularly satisfactory at simulating extreme weather events such as peak rainfalls and minimum/maximum temperatures and is relatively less data demanding than other models (Hashmi et al. 2011); it could effectively generate daily time series of weather data under future climate change scenarios for hydrological impact studies. The review also indicates that the SLURP model has shown its advantages in flexibility of parameter optimization and relatively straightforward water balance calculations in many watersheds around the world (Kite et al. 1994); it is also widely applicable in different sizes and types of watersheds. However, there is a lack of studies that try to take the full advantage of LARS-WG and SLURP in analyzing flood risks. Hence, a combination of LARS-WG and SLURP is desired to offer a cost-effective way of investigating flood flows under climatic changes. No previous studies were found in this particular area. In addition, there are relatively limited studies that are devoted to investigation of flood frequency changes under future climate for the watersheds in the south-central part of China; examination of the related uncertainty effects is especially lacking. In fact, such a region has witnessed anomalously increasing precipitation and rising temperature in flood seasons since the 1990s, which has led to a higher frequency and magnitude of flood events (Zhang et al. 2001). It is desirable for such a region to have reliable scientific ways to help examine the related problems.

Therefore, this study presents a combined LARS-WG and SLURP approach (LW–SLURP) for flood frequency analysis under changing climatic conditions and applies it to the Heshui watershed in Jiangxi Province, China. Uncertainties associated with climate models and emission scenarios will be taken into consideration by adopting multiple combinations of GCMs and climate emission scenarios from LARS-WG. The study results are useful in helping to gain an insight into the flood risk and its uncertainty under future climate change conditions for the Heshui watershed, and the proposed methodology is also applicable to many other watersheds in Southeast Asia with similar climatic conditions.

2. Study area and data

As a major tributary of the Ganjiang River (the seventh largest branch of the Yangtze River), the Heshui River (with source location at 27°24'N, 114°01'E) has a length of 256 km, flowing across one major city (Ji An) and seven counties in Jiangxi Province, China. The watershed to be studied covers the upstream Heshui River before Yongxin County, Jiangxi Province, and has a total drainage area of 2580 km². Figure 1 shows its geographical location and shape. The river flows from west to east, with elevation decreasing from over 1000 m (mountainous areas) to around 110 m (plain terrain in the downstream area). The Heshui watershed belongs to the climate zone with subtropical moist monsoons, an annual-average temperature around 17.8°C, and a relative humidity around 80%. Summer temperature is high, especially in July and August; winter is cool and humid, with little snowfall. The annual-average rainfall is about 1530 mm. The watershed is widely covered by evergreen broadleaf forest, shrubs, and croplands (Huang et al. 2006).

The Heshui watershed at the Yongxin section has been suffering from serious flood problems. Historical flood events have resulted in tremendous damages to the agricultural production, eco-environmental system, and domestic lives. The flood season is normally from April to September, with over 70% in April–June. Yongxin County is the major residential area in the upstream Heshui watershed, with a population around 100 000. The county has flood disasters almost every 2–3 years and large ones every 5–6 years, mostly caused by typhoon rains. The local government has taken great efforts to develop flood emergency management plans to help mitigate flood disasters (YFDMO 2012). From a long-term point of view, climate change may cause significant changes to the hydrological patterns at the local areas. An increase of flood risk would pose a great threat to the local people. It is therefore imperative to
evaluate the potential impact of climate change on food risks in order to support development of long-term flood defense strategies for the local area.

For a climate impact study on flood risks, both weather and hydrometric data are required. The official data from Yongxin hydrological station (location shown in Fig. 1) only consists of rainfall and runoff records from 1988 to 2000. To enrich the rainfall data for the entire catchment, the Asian Precipitation—Highly Resolved Observational Data Integration Towards Evaluation of Water Resources (APHRODITE) data at 0.25° resolution from 1961 to 2007 is collected (Yatagai et al. 2012). The gridded APHRODITE data are a rain gauge–based gridded precipitation dataset using an improved interpolation scheme based on 5000–12 000 local station data over Asia (Yatagai et al. 2012). The data have been validated by Sohn et al. (2012) and Ali et al. (2012), among others. The grids that cover the entire catchment are shown in Fig. 1. Daily mean temperature $T_{\text{mean}}$ at the same resolution and time range is also collected. The APHRODITE project offers daily precipitation $P$ and temperature datasets with high-resolution grids for Asia. Maximum temperature $T_{\text{max}}$, minimum temperature $T_{\text{min}}$, relative humidity $R_h$, and global radiation $R_a$ are obtained from the National Centers for Environmental Prediction (NCEP) Climate Forecast System Reanalysis (CFSR). The data are at a relatively high resolution ($\sim 38$ km) compared with the National Center for Atmospheric Research (NCAR) reanalysis dataset ($\sim 250$ km) and contain climate information from 1979 to 2010 for the entire globe (Saha et al. 2010). Many previous studies, such as Xue et al. (2011), Jakobson et al. (2012), and Meng et al. (2012), have looked into the validation of CFSR. The authors have referred to the Global Weather Data for SWAT website (http://globalweather.tamu.edu/) to gain the required data directly. GIS data, including digital elevation model (DEM) maps and land uses (with 30-m resolutions) for the watershed, are collected from local governments. Future climate data are obtained from LARS-WG database directly.

3. Methodology

a. System framework

Figure 2 shows the framework of the proposed LW–SLURP for flood frequency analysis under climate change. LARS-WG, as a weather generator, will be used to offer climate data from GCM projections forced with specific emission scenarios. The output (including precipitation, maximum temperature, minimum temperature, and radiation), presented as daily time series, will first be used to obtain the mean and dewpoint temperatures based on regression approaches; afterwards, the related weather information will be plugged into SLURP to generate the corresponding real-time river hydrographs. Flood frequency analysis will then follow to analyze the statistics of annual peaks. Because of uncertainty associated with climate change scenarios, multiple-model, multiple-scenario ensembles are normally required to gain a spectrum of possible outcomes. To ensure reliability of both weather generator and hydrological model, historical data are required for model calibration and verification. The detailed procedures are explained in the followed sections.

b. Step 1: Weather generation under climate change based on LARS-WG

LARS-WG was developed by Semenov and Barrow (1997). The foundation of this model is to analyze the statistical properties of daily meteorological variables to reproduce the simulated data based on a pseudorandom generator (Racsko et al. 1991; Semenov et al. 1998). The input and simulated local weather variables include precipitation, minimum temperature, maximum temperature, and solar radiation. Two major procedures are involved in the model: 1) data analysis or model calibration and 2) generation of time series of synthetic climate data. During calibration, the model analyzes the input weather information and estimates the parameters of probability distributions. The LARS-WG adopts semi-empirical distributions to fit wet and dry spell lengths, precipitation amount, minimum temperature, maximum...
temperature, and solar radiation (Semenov et al. 1998). The input values are divided into 23 intervals ranging from minimum to maximum values and are applied for the semiempirical distributions to ensure a high accuracy (Semenov and Stratonovitch 2010). To simulate precipitation, the status of day is determined by the distribution of wet or dry length first. Then the precipitation amount is estimated by separate parameters for each month based on semiempirical distribution. Other variables, like temperature and radiation, are also related to the wet or dry day and are conditioned on the wet or dry spell distribution. In LARS-WG, the minimum and maximum temperatures for dry and wet day are calculated for each month, with autocorrelation and cross-correlation calculated monthly, to enhance the simulation of extreme events (Semenov and Stratonovitch 2010). The simulation of solar radiation is based on normal distribution (Semenov et al. 1998). LARS-WG could consider 15 GCMs to simulate the future situations in the recent version 5.5. Most of the scenarios consider three future time frames: 2011–30, 2046–65, and 2080–99. In this model, the future climate scenarios are adjusted by the monthly “change factors” from GCM results to a historical period for the grid covering the site. LARS-WG uses various hypothetical tests (including a Student’s t test, F test, and chi-squared test) to compare the synthetic data with observed data for the baseline condition (Semenov and Barrow 2002). See Semenov et al. (1998) and Semenov and Stratonovitch (2010) for more technical details.

In this study, the rainfall record of APHRODITE from 1961 to 2007 at the grid covering the Yongxin County is used for site analysis of LARS-WG. The baseline year record is adjusted linearly as the default baseline year is from 1961 to 1990. There are a number of reasons to do this. First, as rainfall is the most important factor in triggering flooding problems, we intend to use a sufficiently long historical record (i.e., 47 years) to ensure the related statistics are most representative of local conditions. Second, it is found that the neighboring APHRODITE grid rainfall data are highly correlated with that in the grid covering the Yongxin County [all correlation coefficients (CCs) >0.97]; therefore, we only use these single-grid rainfall data for training LARS-WG and projecting future conditions. To verify that the grid data are representative of local rainfall data, we have compared the statistics of the grid rainfall with station records from 1988 to 2000 (as shown in Fig. 3). It is found that the monthly mean, standard deviation, maximum value, and skewness for the two types of records are fairly close (the mean relative errors are 2.81%, −9.80%, 0.29%, and 0.005%, respectively). LARS-WG also requires maximum temperature, minimum temperature,
and radiation for site analysis. They are based on CFSR data from 1979 to 2007.

To ensure the results are reliable, we have run the Dixon’s Q test of LARS-WG using different random seeds for at least 10 times. Each time, the significance tests (Kolmogorov–Smirnov) on distributions of rainfall, temperature, and radiation for site analysis. They are based on CFSR dataset from 1979 to 2007.

TABLE 1. GCMs and emission scenarios used in the study (Semenov and Stratonovitch 2010). For time periods, B = 1961–90, T1 = 2011–30, T2 = 2046–55, and T3 = 2080–99.

<table>
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<th>Expansion</th>
<th>Acronym</th>
<th>Resolution</th>
<th>Emissions scenarios</th>
<th>Time periods</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>Commonwealth Scientific and Industrial Research Organisation Mark, version 3.0 (CSIRO-Mk3.0; Australia)</td>
<td>CSMK3</td>
<td>1.9° × 1.9°</td>
<td>A1B, B1</td>
<td>B, T1, T2, T3</td>
<td>Gordon et al. (2002) and CSMD (2005)</td>
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<tr>
<td>Centre National de Recherches Météorologiques Coupled Global Climate Model, version 3 (CNRM-CM3; France)</td>
<td>CNCM3</td>
<td>1.9° × 1.9°</td>
<td>A1B, A2</td>
<td>B, T1, T2, T3</td>
<td>Déqué et al. (1994)</td>
</tr>
<tr>
<td>ECHAM5/Max Planck Institute Ocean Model (ECHAM5/MPI-OM; Germany)</td>
<td>MPEH5</td>
<td>1.9° × 1.9°</td>
<td>A1B, A2, B1</td>
<td>B, T1, T2, T3</td>
<td>Roeckner et al. (1996)</td>
</tr>
<tr>
<td>Bergen Climate Model, version 2.0 (BCM2.0; Norway)</td>
<td>BCM2</td>
<td>1.9° × 1.9°</td>
<td>A1B, B1</td>
<td>B, T1, T2, T3</td>
<td>Furevik et al. (2003)</td>
</tr>
<tr>
<td>Flexible Global Ocean–Atmosphere–Land System Model gridpoint, version 1.0 (FGOALS-g1.0; China)</td>
<td>FGOALS</td>
<td>2.8° × 2.8°</td>
<td>A1B, B1</td>
<td>B, T1, T2, T3</td>
<td>Wang et al. (2004)</td>
</tr>
<tr>
<td>Hadley Centre Global Environment Model, version 1 (HadGEM1; United Kingdom)</td>
<td>HadGEM</td>
<td>1.3° × 1.9°</td>
<td>A1B, A2</td>
<td>B, T1, T2, T3</td>
<td>Martin et al. (2006); Ringer et al. (2006)</td>
</tr>
<tr>
<td>Community Climate System Model, version 3 (CCSM3; United States)</td>
<td>NCCCS</td>
<td>1.4° × 1.4°</td>
<td>A1B, A2, B1</td>
<td>B, T1, T2, T3</td>
<td>Kiehl et al. (1998); Kiehl and Gent (2004); Collins et al. (2004)</td>
</tr>
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</table>

Table 1 lists the detailed scenarios and time periods of interest. In total, 46 scenarios are used for predicting the future rainfall, temperature, and radiation patterns in the studied watershed. The number of years to generate synthetic climate data is 200 for each emission scenario of each GCM.

c. Step 2: Data conversion

As hydrological models have specific requirements on their input variables, data conversion is necessary. The output from LARS-WG generally includes , , and and the required weather input for SLURP includes , , dewpoint temperature , and . The mean temperature is estimated by arithmetic mean of maximum and minimum temperatures (Ma and Guttorp 2013):

where is the mean dry-bulb temperature and is relative humidity. Equation (2) is relatively accurate for approximating the conversion for moist air ( ). In the Heshui watershed, the annual-average is about 80%, and most of the year it is above 50%. For future projections, because of lack of information on relative humidity (as it is not available from LARS-WG), a response surface regression model is proposed to estimate , from other available weather variables (including , , , and ):

As CFSR data offer relative humidity from 1979 to 2010, the dewpoint temperature for such a period can be obtained based on the equation proposed by Lawrence (2005):

where is the mean dry-bulb temperature and is relative humidity. Equation (2) is relatively accurate for approximating the conversion for moist air ( ). In the Heshui watershed, the annual-average is about 80%, and most of the year it is above 50%. For future projections, because of lack of information on relative humidity (as it is not available from LARS-WG), a response surface regression model is proposed to estimate , from other available weather variables (including , , , and ):

where , and and the required weather input for SLURP includes , , dewpoint temperature , and . The mean temperature is estimated by arithmetic mean of maximum and minimum temperatures (Ma and Guttorp 2013):
where $T_{\text{max}}$ and $T_{\text{min}}$ are in degrees Celsius, $P$ is in millimeters, and $R_a$ is in mega joules per square meter. Equation (3) is developed based on CFSR data from 1979 to 2005. Figure 4 shows the verification results using data from 2006 to 2010. The correlation coefficient is found to be 0.967. The major discrepancy is found when $T_{\text{dew}}$ is lower than $-5^\circ C$. For the Heshui watershed, the flood seasons occur mostly from June to September ($T_{\text{mean}} > 20^\circ C$); we believe such a discrepancy would not bring too much error to flood frequency analysis. After data conversion, the $P$, $T_{\text{mean}}$, $T_{\text{dew}}$, and $R_a$ will be used as climate data inputs for the SLURP model.

d. Step 3: Hydrograph generation based on SLURP

The hydrological model used in this study is SLURP, a model developed by Kite et al. (1994). Over recent decades, the model has been widely used in a variety of watersheds of various sizes (e.g., from less than 1000 km$^2$ to more than 275 000 km$^2$) and types (e.g., mountain area and urbanized area). SLURP is a continuous, spatially distributed basin model that uses the parameters from physiographic data to simulate the hydrological cycle from precipitation to runoff (Kite et al. 1994; Kite 1997, 2001; Thorne and Woo 2006). A watershed should be divided into several subwatersheds or aggregated simulation areas (ASAs) based on DEM maps through Topographic Parameterization (TOPAZ), which is a software to treat the DEM data to analyze watershed characteristics. The subwatershed is also classified into different land covers by the data from the digital land cover classification (Kite 2001). SLURP conceptualizes a watershed system into four storage tanks and conducts a vertical water balance based on each of the land covers and ASAs. The technical details of the SLURP model are given in section S1 of the supplemental material.

In this study, evapotranspiration in SLURP is based on the Spittlehouse–Black method (Spittlehouse 1989). The storage routing method is adopted for flood routing. Before future projection, the model is calibrated and verified using observed data. The related climate and hydrometric data ranging from 1988 to 1997 are used for SLURP model calibration, and the data from 1998 to 2000 are used for model verification. The rainfall data are based on both local weather station and grid data from APHRODITE, where the center point of the grid data is assumed to be a point gauge and is combined with local gauges using the Thiessen polygon method (Fiedler 2003). The mean temperature is from APHRODITE and is based on the grid that covers Yongxin County. The dewpoint temperature and global radiation are based on one CFSR grid. The entire watershed has been divided into 19 subwatersheds using TOPAZ (Garbrecht and Martz 1997). Five types of land covers are defined, including tillage land, forest, bushes, urban areas, and meadows. The model optimization for parameter estimation is based on the built-in Shuffled Complex Evolution–University of Arizona (SCE-UA) method (Duan et al. 1994). The Nash–Sutcliffe efficiency (NS) and CC are both calculated by observed and simulated data and are selected to assess the SLURP model performance. The values of NS and CC during calibration stage are found to be 0.696 and 0.893, respectively; those during verification stage are 0.694 and 0.875, respectively. Based on the SLURP simulation, it is found that the fast storage dominantly contributes to the runoff that causes flooding problems (see section S2 of the supplemental material). For future conditions under climate change, the runoff generation mechanism of the hydrological model is assumed to be unchanged. These results show that the SLURP is relatively satisfactory for predicting runoff for the studied watershed and is applicable for projecting future flows, given future climate inputs. The future hydrographs under climate change conditions are obtained by running the calibrated SLURP model using the synthetic (and converted) weather variables from LARS-WG.

e. Step 4: Flood frequency analysis

The annual maximum flow rate of the Heshui is used for flood frequency analysis using the U.S. Geological Survey (USGS) B17 method (USGS 1982). The Pearson type III distribution with log transformation (log Pearson type III) is used as the basic distribution for fitting the annual peak values. The expected moments algorithm (EMA) is used to find the distribution parameters for the station data (England and Cohn 2007).
creased level of uncertainty. In period $T_1$, the upper range does not change much (+3.27%) with regard to the level in period $T_2$, but the lower range would increase by 8.57%.

The uncertainty of the flood frequency curves under different scenarios is found to vary with both flood return periods and projected time periods. The range of flood-peak fluctuations tends to be wider with the increase of the return period. For example, Fig. 6b shows the interval of a boxplot for a 200-yr return (1210.8 m$^3$ s$^{-1}$) would increase by about 4 times wider than that for a 5-yr return (305.9 m$^3$ s$^{-1}$), where the relative change of interval (i.e., normalized interval over median) would be about 1.5 times wider. This may be due to the fact that the flood frequency curve obtained from a Pearson type III distribution has larger deviations at more extreme flood peaks (see Fig. 5). It also appears that the flood peaks in periods $T_2$ and $T_3$ are obviously more uncertain than those in period $T_1$ in terms of both 75th–25th percentiles and whiskers. This implies that different GCMs and emission scenarios tend to lead to more notable deviations when time flows forward to the end of this century. It is hard to say which condition is most likely to occur as the scenarios are evenly distributed, and the scenarios adopted are also subject to selection subjectivity. However, a majority of the results demonstrate that the level of uncertainty of the flood peaks would increase in the middle and end of this century. Although the width of whiskers for $T_3$ is larger than that of $T_2$, most of the flood peaks for $T_3$ are more concentrated than those for $T_2$ (i.e., the box width for $T_3$ is narrower than that of $T_2$). For example, the box widths for 200-yr flood under $T_1$, $T_2$, and $T_3$ are 612.2, 1210.8, and 986.7 m$^3$ s$^{-1}$, respectively, whereas, in light of extreme conditions (i.e., the whiskers), the widths keep increasing (i.e., 1539.6, 2022.8, and 2344.3 m$^3$ s$^{-1}$, respectively). In addition, an insight into the extreme conditions could provide local government a glimpse of what could be the worst scenario. From Fig. 6, the maximum values of 50-yr flood peaks for $T_1$, $T_2$, and $T_3$ are 25.18%, 31.00%, and 44.46% higher than those of the baseline levels. This implies that for the next 20 years, the local watershed may experience up to a 25% increase of flood peaks and a further increase up to 45% at the end of this century. The related results provide some useful information for understanding the possible risks of floods in the future. However, considering the large uncertainty originated from climate models, further efforts of the cost–benefit analysis are needed before a practical decision can be made in adaptation planning.

4. Result analysis

The baseline flood frequency curve is generated based on the SLURP-simulated flow peaks, using 200-yr synthetic climate data as inputs. The synthetic data match the site statistics established based on historical records. Figure 5 shows the plotting positions for the annual flow peaks. It appears that the local flow conditions fit the Pearson type III distribution well. The 200-yr return flood exceeds 4000 m$^3$ s$^{-1}$ for the local area. The fitted flood frequency curve is found to be consistent with the local governmental record used for flood defense projects (YFDMO 2012). The flows under various scenarios are obtained from running hydrological models. The time periods of interest include 2011–30 ($T_1$), 2046–65 ($T_2$), and 2080–99 ($T_3$). Each time period has a 200-yr synthetic time series to ensure a reliable generation of flood frequency curves.

Figure 6 shows the boxplots of flow peak variations under all GCM scenarios over the three time periods. It appears that, although the results vary considerably, there is a general increasing trend of flood peaks from $T_1$ to $T_3$ for all shown return years (i.e., 5, 10, 25, 50, 100, and 200). Taking a flood with 200-yr return period as an example, the relative increase of medians in comparison to the baseline for $T_1$, $T_2$, and $T_3$ are 5.23%, 4.08%, and 12.92%, respectively. The 75th percentiles of the increase for $T_1$, $T_2$, and $T_3$ are 11.91%, 21.97%, and 25.24%, respectively, and the 25th percentile ones are $-2.58%$, $-6.69%$, and $1.88%$. This demonstrates that flood risk would generally increase, but with an increased level of uncertainty. In period $T_1$, about 75% of scenarios imply an increased risk of flood peaks, while the others show a decreasing trend. In the 2050s, the range of changes would become considerably wider. The lower-range (25th percentile) flood peaks would drop by 4.11%, but the upper range (75th percentile) shows an increase of 10.06%. In period $T_3$, the upper range does not change much (+3.27%) with regard to the level in period $T_2$, but the lower range would increase by 8.57%.

FIG. 5. Plotting position based on 200-yr simulated flow record for baseline condition. See local governmental report (YFDMO 2012) for official record.

FIG. 6. Plotting position based on 200-yr simulated flow record for baseline condition. See local governmental report (YFDMO 2012) for official record.
Figure 7 gives a separate illustration of flood-peak variations under different emission scenarios and GCMs. It is indicated that, for the longer-term predictions (i.e., $T_2$ and $T_3$), MPEH5 suggests a notable increase of flood risks and projects the most serious condition (6176.7 m³ s⁻¹ for 200-yr return flood) under scenario A2 2080–99. FGOALS also leads to a relatively higher level of flood-risk projections under scenario B1 for $T_1$, $T_2$, and $T_3$, among which $T_2$ seems to have a higher flood risk; predictions under scenario A1B by FGOALS suggests a more intense flood risk during 2011–30, but decreased risks in the longer term. CSMK3 seems to suggest more conservative changes of flood risks compared with others. Under scenarios A1B and B1, it projects either a lower or equivalent level of flood risks compared with baseline levels. The projected results from NCCCS also tend to be fairly conservative as most of the flood risks would not change significantly and the projection under B1 in period $T_2$ would even be about 25% lower than the current level. However, under A1B during 2046–65, it suggests a significantly increased flood risk. Generally, a majority of projections suggest an increase of flood peaks for different return periods.

To further explore the relationships between rainfall pattern changes and flood risks, a linear regression analysis is conducted based on rainfall changes projected from 46 scenarios (in LARS-WG) and the resulting flood frequency changes. Such relationships are revealed because the rainfall has the most dominant effect on flood frequencies, in comparison to temperature and radiation. Further analysis of the correlation between extreme daily rainfall and flood events is given in section S2 of the supplemental material. Because most of the floods occur in the flood season (from May to August), we use the relative average rainfall changes during flood season as the independent variable and the relative average change of flood peak under a specific return year as the dependent variable. Figure 8 shows the related regression outputs under a number of return years. It shows that these two terms are highly correlated. For a 1% increase of average rainfall during flood season, the corresponding flood-risk increase would be 1.86%, 1.99%, 2.05%, and 2.12% for the 10-, 50-, 100-, and 200-yr return flood. The errors mainly come from the influence of temperature and radiation. The result is useful, as we could directly use it to estimate the
variation of rainfall patterns on changes of flood frequencies, when other GCMs or RCM scenarios are available.

5. Discussion

The study provided a demonstration of a systematic way of conducting flood frequency analysis under climate change, taking full advantage of LARS-WG and SLURP. The links between the two types of models were explored with the aid of regression models. No such study has previously been conducted, and the framework is promising for use in many other regions around the world, especially Southeast Asia, where the regression errors from dewpoint estimation would be small (due to higher range of temperature) and the related data are relatively scarce. However, the study relied on the LARS-WG’s embedded database with

Fig. 7. Flood frequency results under projections with different emission scenarios (a),(d),(g) A1B; (b),(e),(h) B1; and (c),(f),(i) A2; for (top) 2011–30, (middle) 2046–65, and (bottom) 2080–99.
limited factors to project for future conditions. This may not be fully representative of all possible changes of future climate.

There are also a number of limitations for this study. First, the projection of future climate changes is mainly based on the changes of mean monthly rainfall, temperature, and radiation (whatever LARS-WG has). Further consideration of other weather characteristics (like standard deviation and skewness of rainfall) is difficult and has to be based on specific GCM outputs and downscaling tools. Second, because of data limitations, we have applied grid weather data to fulfill the needs of the hydrological model and weather generator. The result is relatively satisfactory, as we have acceptable verifications for both hydrological model and flood frequencies. This may because the studied watershed is not too large to have notable distributed rainfall patterns. We believe the model performance can be further improved, if more local data are available. However, as data scarcity is quite a common problem for many areas, especially South Asian countries, grid data could still be considered an alternative for future predictions if the rainfall characteristics can been well verified to be representative for local conditions.

Furthermore, possible land use changes in the future could also affect the rainfall–runoff processes in a complicated way (Zhang et al. 2012). For example, Brown et al. (2005) indicated that the forest-type land generates more water evaporation than crop land, and land with more agricultural farming would increase the water consumption for irrigation; Shi et al. (2007) pointed out that the urbanization would increase the maximum flood discharge and decrease the runoff confluence time. In China, transferring forest to agriculture was encouraged until the end of 1990s; afterward, the policy started to emphasize the return to forest/grassland (Wang et al. 2004; Zhang et al. 2012). In our study area, most of the land is covered by crops and forest, and the urban area is a very small fraction of total area (less than 1%). A possible increment of the urbanized area and population growth in the future could lead to the transfer of part of the crop-/forestland into industrial and/or urban areas. However, this may not cause significant effects on the flood risks. To gain a deeper understanding on the land use impact in the future, a projection of future land use
types, local economic condition, governmental policies, and population size are necessary. In our future work, linking human activity and climate change to flood-risk assessment would be interesting and may bring more reliable conclusions.

By comparing the median value of multiple ensembles with baseline data, the flood risk at the study watershed is expected to increase under most of the concerned GCM scenarios. The study results also show a wide range of uncertainty. On the one hand, this could avoid planning that is based on pure historical record or a single “best estimate” scenario, encouraging adaptation efforts that better reflect the changing nature of the risk (Lawrence et al. 2013). On the other hand, the uncertainty arising from the GCM scenarios shows potential variability of flood risk in the future; water managers need to perform a careful trade-off analysis between mitigation of such risk and available budget in adaptation. In terms of water variability for drought risk assessment (like reservoir, aquifer storage design, and water supply issues), it is not recommended to use the proposed method in the current stage, as LARS-WG, version 5.5 (which is adopted in this study), does not provide relative changes in durations of both wet and dry spells for most of the GCM scenarios (Semenov and Stratonovitch 2010). Should such information become available in the near future or there is an updated version of the database, it is more reliable to look into drought effects quantitatively. However, we believe the proposed LARS-WG approach is valid for flood-risk analysis as peak flows are more sensitive to relative change in monthly mean of rainfall.

6. Conclusions

This study investigated the flood frequency changes under climate change for the Heshui watershed covering Yongxin County, Jiangxi Province, China, based on a combined LARS-WG and SLURP approaches. LARS-WG, as a weather generator, was used to offer climate data from GCM projections forced with a specific emission scenario. The output was plugged into the hydrological model to generate the corresponding runoff information. Flood frequency analysis was followed to analyze the statistics of annual peaks. The study indicated that there is a general increasing trend of flood peaks in the studied watershed to the end of this century, although the uncertainty range derived from multiple scenarios was fairly wide. A 200-yr return flood for $T_1$ (2011–30), $T_2$ (2046–65), and $T_3$ (2080–99) would have relative increases of flood level by 5.23%, 4.08%, and 12.92%, respectively; those under the most extreme condition (i.e., worst scenario) would be 25.18%, 31.00%, and 44.46%, respectively. Various GCMs and emission scenarios suggested different results. But MPEH5 was found to give a more worrying increase of flood risks, and CSMK3 and NCCCS were relatively conservative.

In terms of methodology, this study improved upon the previous works in a number of aspects. First, a combined LARS-WG and SLURP approach (LW–SLURP) was adopted for flood frequency analysis under changing climatic conditions, and its applicability was proven effective for the watershed in the south-central part of China. In particular, the linkage between LARS-WG and SLURP was made possible through a number of proposed data conversions (like the regression analysis for dewpoint temperature), which were not reported before. Second, the uncertainties associated with climate models and emission scenarios were well addressed by the proposed method. In fact, among many alternatives to weather generators, only LARS-WG included a fairly comprehensive database that embeds over 35 climate change scenarios from 15 GCMs used in the Fourth Assessment Report (AR4) of the Intergovernmental Panel on Climate Change (IPCC) over the globe and many RCM results for European countries (Semenov and Stratonovitch 2010). The database is still growing and is expected to offer a “computationally cheaper” option than dynamic downscaling in helping hydrological impact studies in consideration of uncertainty from GCM scenarios. Third, it was recognized that the SLURP model applied an embedded optimization scheme to help identify a number of prescreened and most sensitive parameters in hydrological modeling, and this could save a lot of effort in rainfall–runoff calibration, compared with other alternative models like SWAT (Kite et al. 1994).

From this study, it was found that the uncertainties associated with GCMs under different emission scenarios were quite significant; this could lead to a spectrum of possible consequences on the flood risks. It is generally difficult to judge which scenario is most likely to occur as they do not have a specific distribution. However, the general trend of a flood-risk increase has been observed from the median of the projected results in both the short and long term of this century, and the worst scenario of flooding risk increase is quite alarming. Another finding from this study is that there exists a high correlation between extreme daily rainfall and flood events. The relative change of rainfall during flood season is somewhat linearly related to the relative change of annual flood peaks. This could potentially provide a rule-of-thumb method to roughly estimate the flood risks based on projected rainfall information.
only. Generally, the methodology framework is believed to be applicable to many other areas, especially Asian countries, as the CFSR and APHRODITE data are readily available for such a region.

There are a number of future works that could be carried out to refine and improve this study. First, LARS-WG is limited to prediction of a single site. This works for a large watershed with multiple weather stations considering spatial independence, or a relatively small watershed that is assumed to be in a homogenous weather condition (like the work in this study). For whatever watersheds with weather stations showing significant spatial correlations, a multisite weather generation method needs to be explored. Second, this study considered only uncertainties from global circulation models and emission scenarios. The uncertainty originated from modeling (including weather generation, hydrological modeling, and flood frequency analysis) itself is yet to be considered.

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REFERENCES


Ali, G., G. Rasul, T. Mahmood, Q. Zaman, and S. B. Cheema, 2011: itself is yet to be considered. Hydrological modeling, and flood frequency analysis


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