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IMPACT OF DENSITY AND LOCATION OF RAIN GAUGES ON PERFORMANCES OF HYDROLOGICAL MODELS

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Abstract

Hydrological models are important tools for flood forecasting and the assessment of water resources under current and changing climate. The accuracy of hydrological models is considerably affected by uncertainties and errors of input data. The objective of this study is to investigate how the input of precipitation data would impact the results of lumped and distributed hydrological model simulations. The Xiangjiang River basin, located in southern China, is used to demonstrate the methodology and discuss the results of using five kinds of precipitation datasets: (1) the rain gauge network composed by 185 gauges, (2) the global satellite based Tropical Rainfall Measuring Mission (TRMM) 3B42 dataset, (3) the global reanalysis Water and Global Change Forcing Data (WFD) dataset, (4) the stochastically diluted rain gauge networks, and (5) the optimal diluted rain gauge networks using Entropy method. Two hydrological models are applied for this purpose: the lumped Xinanjiang Model and the distributed SWAT Model.

The study focuses on three aspects which are presented in three papers. Paper I studies the suitability of global grid data (original and bias corrected) in hydrological modelling in the study region with different temporal resolutions and spatial scales. Linear and non-linear bias adjustment methods were used to correct the bias of first and second moment of the TRMM and WFD datasets grid by grid. In hydrological modelling, the discharge was simulated by daily and monthly steps using the original and bias corrected TRMM 3B42 and WFD datasets. The evaluation of the performances of the two hydrological models showed that the linearly corrected WFD data were reasonably suitable for daily step simulation in Xinanjiang Model and produced satisfactory results in monthly step simulation in both hydrological models. However, good performance can be achieved using nonlinearly corrected TRMM data for monthly streamflow simulations in Xinanjiang Model and linearly corrected TRMM applied in distributed SWAT Model.

Paper II evaluates the stochastically diluted rain gauge network on discharge simulation and investigates the effects of the density and location of rain gauges on the performances of hydrological modeling. The results showed that the location and density of rain gauges have considerably impact on the simulation results of lumped hydrological models. Rigorous evaluation of the influence of different rain gauge density and distribution on the model performance, as shown by the simulated runoff compared with the observed runoff, improved gradually with increasing number of rain gauges up to some threshold, beyond which the model performance did not show considerable improvements.

Paper III uses the entropy theory based multi-criteria method to design an optimal distribution of rain gauge networks with a minimal number of rain gauges to provide reliable precipitation estimates with both areal mean values and spatial-temporal variability. The entropy theory based multi-criteria method simultaneously considered the information derived from rainfall series and minimizing the bias of areal mean rainfall as well as minimizing the information overlapped by different gauges to resample the rain gauge networks with different gauge densities. The discharge simulations showed that the lumped model using different optimized networks performed stable results while the performance of the distributed model kept on improving as the number of rain gauges increases.

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Contents

Part A

Introduction and synthesis

1 Introduction

Precipitation data collected over a river basin constitutes the fundamental inputs for the design of key water resources projects such as reservoirs, water distribution systems, irrigation networks, study of climate change impact on water resources, etc. Hydrological models are valuable tools for the users of precipitation data in numerous fields (e.g. hydrologists, agronomists, climatologists, water resources managers and planners, researchers of numerous organizations, and decision makers in government and non-government organizations etc.). The use of precipitation measurements as a major input for hydrological models has enhanced the need for point and areal measurements that are more representative for "true" precipitation.

Many hydrologists are focused on efficiency in hydrological modelling, and the accuracy of the hydrometeorological data plays an important role in enhancing the performance of hydrological simulations. Hydrologic modelling studies indicate that errors in hydrometeorological data, especially those in precipitation data are the main source of the errors in hydrological modelling (Seo et al., 2003). Therefore, one of the most important factors in successful hydrological simulation is to get reliable and representative precipitation data. Traditionally, rain gauge networks provide direct access to precipitation data. However, the development of technology has resulted in many indirect methods which play a more and more important role in providing precipitation data. Examples of such technological advances in precipitation observation include: remote sensing satellites which provide real time precipitation monitoring with high temporal resolution; the radar rainfall data which deliver local precipitation measurement at a high spatial-temporal resolution; and the reanalysis datasets which provide long-term historical precipitation observations globally.

Rain gauges provide rainfall measurements at individual points, but there is a challenge in using gauged data to estimate rainfall at basin level with appropriate spatial and temporal scales (Sawunyama and Hughes, 2008). With technological advancements, high resolution global grid rainfall datasets are currently available as indirect precipitation information measurements substitute the rain gauges. There are many global rainfall databases (e.g. the Global Precipitation Climatology Project (GPCP), the Global Precipitation Climatology Centre (GPCC), the Climatic Research Unit (CRU) precipitation database, the Climate Prediction Centre of NOAA (National Oceanic and Atmospheric Administration) Merged Analysis of Precipitation (CMAP), etc.) are applied in hydrological researches, however, their usefulness in driving hydrological models at basin scale has to be evaluated (Cheema and Bastiaanssen, 2012) due to the mismatch between the rainfall estimates from global rainfall databases and the rain gauges which unavoidably lead to distrust in both datasets (Ciach et al., 2000; Grimes et al., 1999; Omotosho and Oluwafemi, 2009). Many studies have compared the differences between the various precipitation datasets and rain gauge data as well as their impact on hydrological modelling (e.g. Fekete et al., 2004; Abdella and Alfredsen, 2010; Li et al., 2013). They have shown that global precipitation products can be used as a source information but need calibration and validation due to the indirect nature of the radiation measurements. However, although these precipitation datasets generally agree in their temporal trends and spatial distribution, remarkable differences at basin scales can be observed (Costa and Foley, 1998; Oki et al., 1999; Adler et al., 2001).

Due to the fact that precipitation gauging stations are widely used as direct precipitation measurement for monitoring rainfall at river basin scale, a well-designed rain gauge network should be able to provide appropriate information for different users and applications. However, geographical and economic constraints often limit the ideal gauge density and location, such that there are more rain gauges in the plains and more developed areas but less in the mountain and undeveloped areas. In addition, most river basins of the world are in general poorly gauged or ungauged, and most rain gauge networks applied for hydrological purposes are largely inadequate according to the most dilute density requirements of World Meteorological Organization (WMO, 1994). Moreover, many non-hydrological factors considerably impacted the rain gauge network design, e.g. accessibility, cost and easiness of maintenance, topographical aspects, etc. This situation often results in challenges in estimating water resources and in flood control as these primarily depends on an appropriate rain gauge network to supply adequate information. A well designed rain gauge network with proper gauge density and distribution is therefore a key factor in providing precipitation information at the desired spatial-temporal scales in a catchment.

Rain gauge network design involves the determination of the number and location of stations necessary for achieving the required accuracy (Bras, 1990) and meet the objective of information provided by the network as efficiently and economically as possible (Hackett, 1966). Various approaches have therefore been applied in designing optimal rain gauge network to yield greater precision of rainfall estimation with minimum cost (e.g. Pardo-Igúzquiza, 1998; Patra, 2001; St-Hilaire et al., 2003; Dong et al., 2005; Anctil et al., 2006; etc.)

Precipitation gauge network structure is not only dependent on the station density; station location also plays an important role in determining whether information is gained properly. Gupta et al. (2002) and Yatheendradas et al. (2008) pointed out that rapidly changing patterns of precipitation over mountains are poorly monitored, and there are gaps in the information important to the modelling of runoff generation which makes it difficult to obtain sufficient leading time and accuracy on hydrological forecasts. Consequently, the design of hydrological measurement networks has received considerable research attention. The optimization of rain gauge network by finding ideal locations of a limited number of rain gauges which provide sufficient spatial and temporal rainfall information is therefore an important issue in the application of hydrological modelling at river basin scale.

2 Scope of the thesis

This thesis has the main goal of investigating the impact of precipitation inputs on performances of hydrological models. This will be achieved through the evaluation of the influence of the different formulations of precipitation data on the performance of different hydrological models. The investigation focuses on three aspects that are important in the performance of hydrological models:

(1) Test the suitability of satellite based/reanalysis global precipitation datasets for hydrological modelling at different spatial and temporal scales.

(2) Optimize the rain gauge network by using two methods: the Transcendental and Posteriori methods (here, the two words, Transcendental and Posteriori, are appropriated from probability theory). In the Transcendental Method, a set of optimized rain gauge networks is designed prior to hydrological modelling, and then the optimized networks are tested in hydrological modelling to evaluate their performances in streamflow simulations. In the Posteriori Method, the rain gauge networks are stochastically resampled and the best one is selected by evaluating the performances of hydrological models.

(3) Determine the characteristics of the resampled rain gauge networks that produce good hydrological modelling performances.

To achieve the above study objectives, three research papers constitute the scope of the present thesis as follows:

In paper I, an investigation is carried out with the comparison of the original and bias corrected global gridded precipitation datasets, Tropical Rainfall Measuring Mission (TRMM) and Water and Global Change Forcing Data (WFD) with gauged precipitation. The study also evaluates the usefulness of gridded precipitation datasets for hydrological simulations using the distributed SWAT (Soil and Water Assessment Tool) Model and lumped Xinanjiang Model in Xiangjiang River basin, Southern China. First, the daily and monthly precipitations from the three datasets are compared using carefully selected statistical indices. Two widely used bias adjustment methods (linear and non-linear methods) are then applied on the global gridded datasets (TRMM and WFD). The gauged and original and bias adjusted global grid precipitations are finally tested in forcing the lumped (Xinanjiang Model) and distributed (SWAT Model) hydrological models.

In paper II, a Posteriori Method is applied to examine the influence of rain gauge density and distribution on the performance of the widely used lumped hydrological model—Xinanjiang Model in simulating the streamflow in Xiangjiang River basin in southern China. In this study, the rain gauge networks with various gauge densities were stochastically designed. Then, the mean areal rainfalls derived from the designed networks were estimated by different rain gauge densities using various statistical indices as evaluation criteria. Finally, the influence of different rain gauge density and distribution on the model performance was rigorously evaluated.

In paper III, a Transcendental Method was carried out based on a dense rain gauge network of 185 rain gauges in Xiangjiang River Basin, southern China to resample the rain gauge network. This study used an entropy theory based multi-criteria method which simultaneously considers the information derived from rainfall series and minimizes the bias of areal mean rainfall as well as the information overlapped by different gauges to resample the rain gauge networks with different gauge densities. The optimal networks were again tested using the lumped Xinanjiang and distributed SWAT hydrological Models. The results indicate that the Transcendental Method (entropy theory based multi-criteria strategy) provides an optimal design of rain gauge network which is of vital importance in regional hydrological study and water resources management.

3 Study area and data description

3.1 A general introduction of the Xiangjiang River basin

The Xiangjiang River basin, with a total area of 94660 km^2 and a total river length of 856 km, was selected as the area of interest based on the following reasons:

(1) The size of Xiangjiang River basin is medium compared with other river basins in China. This is very important for achieving the objectives of the study. On one hand, if the river basin used in the study is very small, the spatial variability of the precipitation is not obvious enough for testing the impact of rain gauge location and density on hydrological modelling. On other hand, if the river basin is very large, the network in the basin with dense enough rain gauges is unavailable for the study.

(2) The Xiangjiang River basin has variety of complex topography including mountains, hills and plains which is important for determining the locations of the rain gauges in the diluted rain gauge networks.

(3) The river basin is located in humid southern China typically with strong precipitation-runoff relationship, i.e. the streamflow in the basin is mainly produced by rainfall, which represents the majority of river basins in China.

(4) The river basin has a high quality and densely distributed hydro-meteorological network that serves as excellent region for performing the planned study objectives.

3.1.1 Location and topography

Xiangjiang River basin (Figure 1) is one of the main tributaries of Yangtze River which is located between 24°-29°N and 110°30'-114°E in the central-south China with an area of 94,660 km^2. The basin is surrounded by mountains in the east, south and west. Mountains (with mean elevation > 200 m a.m.s.l. (above mean sea level)) and hills (with mean elevation between 100 and 200 m a.m.s.l.) are mainly located in the upstream and the plains (with mean elevation < 100 m a.m.s.l.) are located in the downstream. The basin shows evident characteristics of mountain streams in the upstream branches and the rolling terrain accelerate the rainfall convergence and the variation of water level and runoff.

3.1.2 Temperature and precipitation

Xiangjiang River basin is characterized by warm and wet summers (May to September) and moderately cold and wet winters (December to February) (Figure 2). The average annual temperature is 17.2 °C (1965–2005). The basin is heavily influenced by monsoon climate, which brings heavy rainfall from the south in summer (Figure 3). The mean annual precipitation is in the range of 1400 to 1700 mm, of which approximately 70% occurs in the main rain season from April to September. The precipitation is spatially inhomogeneously distributed over the Xiangjiang River basin (Figure 4) with areas in the south having higher rainfall than in the north and west. This difference is largely due to the topographical influences that limit the conveyance of moist winds carried by the monsoon from the Pacific Ocean which resulting in complex precipitation variation in this area.

3.1.3 Surface runoff

The discharge of Xiangjiang River is mainly derived from rainfall. The Flood and dry seasons' flow of the trunk stream and its branches in the drainage area are highly related to the temporal and spatial distribution of rainfall. There is also a marked difference in runoff distribution among different seasons with about 68% of the total runoff volume occurring during the wet season (April-September) with 50% of the flooding events occurring in June and July. The dry season is from October to March the next year. The period from April to June is therefore defined as a high-flow period, during which the Xiangjiang River has an average discharge of approximately 2590 m^3/s (at Xiangtan gauging station), whereas the period from November to January is defined as a low-flow period, during which the discharge is at its lowest (approximately 800 m^3/s) for the year (Figure 3).

3.2 Data description

(1) The rain gauges

A high densely distributed rain gauge network which consists of 185 rain gauges (Figure 1) with long term high quality precipitation data (without missing data) from 1st January 1963 to 31st December 2005 is used as the benchmark precipitation input for analyzing the characteristics of the precipitation of Xiangjiang River basin and for calibrating and validating the Xinanjiang Model and SWAT Model.

(2) The global grid precipitation datasets: TRMM 3B42 and WFD datasets

TRMM dataset is a number of climate data products produced from the passive microwave (TMI) and precipitation radar (PR) sensors on board the Tropical Rainfall Measuring Mission (TRMM) satellite launched in November of 1997 (Kummerow et al., 1998; Iguchi et al., 2000). The TRMM project aims to provide small-scale variability of precipitation by frequent and closely spaced datasets which uses a combination of microwave and infrared sensors to improve accuracy, coverage and resolution of its precipitation estimates (Kummerow et al., 2000). However, the ability of TRMM to specify moderate and light precipitation over short time intervals is poor (Huffman et al., 2007; Li et al., 2013). The TRMM 3B42 dataset, covering from 1st January 1997 to 31st December 2008 and 50°S–50°N, is one of the TRMM Rainfall Products which uses the TMI 2A12 rain estimates to adjust high temporal resolution (3-hourly or higher) IR rain rates over daily gridded 0.25×0.25 degree latitude/longitude boxes. It has been used to drive distributed hydrological models in large river basins as well as in flood modelling (Huffman et al., 2007, 2010) (in the following text, TRMM 3B42 is abbreviated as TRMM).

WFD dataset was developed by the WATCH project (Weedon et al., 2011) as input for large-scale land-surface and hydrological models. WFD is named as reanalysis data in the literature which is weather observation data assimilated into global grids by a numerical atmospheric model. The WFD dataset, from 1st January 1958 to 31st

December 2001, consists of meteorological variables needed to run hydrological models, including 2 m air temperature, dew point temperature and wind speed, 10 m air pressure and specific humidity, downward long wave and shortwave radiation, rainfall and snowfall rates (Li et al., 2013). As a global reanalysis data package, the WFD dataset has been applied in many research fields, such as the impact of climate change on hydrometeorological droughts and floods (e.g. Van Huijgevoort et al., 2011; Vrochidou et al., 2013; Ward et al., 2013;); the changes of snow cover and glacier under changing climate (e.g. Siderius et al., 2013; Dankers et al., 2011); the global water balance and water vapour flux (e.g. Harding et al., 2011; Haddeland et al., 2011; Ward et al., 2014) and hydrological model calibration (e.g. Gudmundsson et al., 2012; Stahl et al., 2012; Piani et al., 2010a), etc.

4 Methodology

4.1 Hydrological models

It is generally recognized that simultaneous use of both conceptual and physically-based (or deterministic) hydrological models in the analysis of hydrological processes is necessary to produce the best scientific and practical information for hydrology (Yevjevich, 1972). Therefore, in this study, the lumped Xinanjiang model and distributed SWAT Model were selected as the precipitation-runoff models to demonstrate the proposed study approach and verify the results from the statistical analysis.

4.1.1 Xinanjiang Model

The Xinanjiang model was developed in 1973 and the English version was first published in 1980 (Zhao et al., 1980). Its main feature is the concept of runoff formation on repletion of storage, which means that runoff is not produced until the soil moisture content of the aeration zone reaches field capacity, and thereafter runoff equals the rainfall excess without further loss. The inputs to the model are daily areal precipitation and the measured daily pan evaporation and the daily discharge data is used for model calibration and validation. The outputs are the basin outlet discharge, and actual evapotranspiration, which is the sum of the evapotranspiration from the upper soil layer, the lower soil layer, and the deepest layer (Zhao, 1992; Zhao et al., 1995).

The model has been applied successfully over very large areas since it was published including all of the agricultural, pastoral and forested lands of China except the loess. The model is mainly used for hydrological forecasting (Li et al, 2009; Liu et al, 2009; Yao et al, 2009). Use of the model has also spread to other fields of application such as water resources estimation, design flood and field drainage, water project programming, hydrological station planning, water quality accounting, etc. (Hu et al., 2005; Ren et al., 2006; Bao et al., 2011). The US

National Weather Service River Forecast System also reported of its good performance in the arid Bird Creek watershed in the United States (Singh, 1995).

4.1.2 SWAT Model

The Soil and Water Assessment Tool (SWAT) model, which conducted by the USDA Agricultural Research Service (ARS) has gained international acceptance as a robust interdisciplinary watershed modelling tool, is a river basin scale model developed to quantify the impact of land management practices in large, complex watersheds (Reyes et al., 2007).

SWAT Model is a distributed basin-scale, continuous-time model that operates on a daily time step and is designed to predict the impact of management on water, sediment, and agricultural chemical yields in gauged/ungauged watersheds (Arnold et al., 1998). The model is physically based, computationally efficient, and capable of continuous simulation over long time periods. Major model components include weather, hydrology, soil temperature and properties, plant growth, nutrients, pesticides, bacteria and pathogens, and land management (Coffey et al., 2010). In the SWAT Model, a watershed is divided into multiple sub-watersheds, which are then further subdivided into Hydrologic Response Units (HRUs) that consist of homogeneous land use, management, and soil characteristics (Flügel, 1997). The HRUs represent percentages of the sub-watershed area and are not identified spatially within a SWAT simulation (Flügel, 1995; 1997). When using SWAT Model for water balance studies, climatic inputs include daily precipitation, maximum and minimum temperature, solar radiation data, relative humidity, and wind speed data, which can be input from measured records and/or generated using Weather Generator (GA) in the model. Relative humidity is required if the Penman-Monteith or Priestly-Taylor evapotranspiration (ET) routines are used; wind speed is also needed if the Penman-Monteith method is used (Reyes et al., 2007). Measured or generated sub-daily precipitation inputs are required if the Green-Ampt infiltration method is selected. The average daily air temperature is used if precipitation is in the form of snowfall. The maximum and minimum temperature inputs are used in the calculation of daily soil and water temperatures. Generated weather inputs are calculated from tables consisting of 13 monthly climatic variables, which are derived from long-term measured weather records.

The overall hydrologic balance is simulated for each HRU, including canopy interception of precipitation, partitioning of precipitation, snowmelt water, and irrigation water between surface runoff and infiltration, redistribution of water within the soil profile, evapotranspiration, lateral subsurface flow from the soil profile, and return flow from shallow aquifers. Two options exist in SWAT for estimating surface runoff from HRUs, which are combinations of daily or sub-daily rainfall and the USDA Natural Resources Conservation Service (NRCS) curve number (CN) method (USDA-NRCS, 2004) or the Green-Ampt method (Green and Ampt, 1911; Mockus, 1969; Jha et al., 2004;). Canopy interception is implicit in the CN method, while explicit canopy interception is simulated for the Green-Ampt method (King et al., 1999).

4.1.3 Model calibration and evaluation

The Nash–Sutcliffe Model Efficiency Coefficient (Nash and Sutcliffe, 1970) was taken as the objective function for calibrating the Xinanjiang Model and SWAT Model. The Genetic Algorithm and SUFI2 (Sequential Uncertainty Fitting version 2) Algorithm provided by SWAT CUP (SWAT Calibration and Uncertainty Procedures) were used for calibrating the Xinanjiang Model and SWAT Model respectively. All the 15 parameters of the Xinanjiang Model (Table 1) and the 12 most sensitive parameters of the SWAT Model (ranked by CN2, SOL_AWC, GWQMN, ESCO, GW_DELAY, ALPHA_BF, SOL_BD, SOL_K, REVAPMN, SLSUBBSN, SURLAG and GW_REVAP) (Table 2) were selected for the calibration process. The same initial values and range of parameters were applied in calibrating the different data based models.

The hydrological models performances were evaluated by using two popularly adopted indices, Nash-Sutcliffe Model Efficiency Coefficient (E_{ns}) and Relative

Volume Error (R_E). The E_{ns} determines the relative magnitude of the residual variance ("noise") compared to the measured data variance ("information").

$$E_{ns} = 1 - \frac{\sum_{t=1}^{N}(Q_s(t) - Q_o(t))^2}{\sum_{t=1}^{N}(Q_o(t) - \overline{Q_o})^2} \tag{1}$$

Where $Q_o(t)$ and $Q_s(t)$ are the observed and simulated discharges at time t respectively. $\overline{Q_o}$ is mean observed daily runoff and N is the total number of days.

The R_E is used for quantifying the volume errors. It can vary between ∞ and $-\infty$ but performs best when a value of zero is generated since no difference between simulated and observed discharge occurs (Janssen and Heuberger, 1995). A Relative Volume Error ranges between -5% and +5% indicates that a hydrological model performs well while Relative Volume Error between +5% and +10% or between -10% and -5% indicate a model with reasonable performance (Wu and Wu, 2011).

$$R_E = \left[\frac{\sum_{t=1}^{N}(Q_s(t) - Q_o(t))}{\sum_{t=1}^{N}Q_o(t)}\right] * 100\% \tag{2}$$

The notations are as defined above.

4.2 Bias adjustment methods

Due to the fact that global gridded precipitation datasets have biases and random errors which are caused by various factors like sampling frequency, nonuniform field-of-view of the sensors, and uncertainties in the rainfall retrieval algorithms (Wilheit et al., 1994; Adeyewa et al., 2003), many algorithms have been developed for bias correction (Yang et al., 1999; Li et al., 2010; Piani et al., 2010b; Dosio and Paruolo, 2011; Kang and Merwade, 2014). In this study, two widely used bias correction algorithms were adopted to correct the biases of TRMM and WFD precipitation data:

4.2.1 Linear bias correction method

The linear bias correction method (Teutschbein and Seibert, 2012) is simple and widely used, in which TRMM/WFD daily precipitation amounts, P, are transformed into P^* such as $P^*=aP$, using a scaling parameter, $a=\overline{O}/\overline{P}$, where $\overline{O}$ and $\overline{P}$ are monthly mean gauged and TRMM/WFD precipitation respectively. The monthly scaling factor is applied to each uncorrected daily TRMM/WFD data of that month to generate the corrected daily time series.

4.2.2 Nonlinear bias correction method

Leander and Buishand (2007) developed a nonlinear bias correction algorithm to correct the precipitation P in the following form:

$$P^*=aP^b \tag{3}$$

Where P^* and P are the corrected and the original TRMM/WFD precipitation data, respectively. The parameters a and b are obtained for each grid point of the considered domain on a monthly basis by using daily data iteratively with a root finding algorithm (Brent, 1973):

$$b(x,i): CV(P^{b(x,i)}) = CV(P_{obs}) \tag{4}$$

$$a(x,i): \overline{a(x,i)P^{b(x,i)}} = \overline{P_{obs}} \tag{5}$$

Where x is the grid point to be corrected, i represents the month, the overbar alludes to the monthly average, and $CV()$ is the coefficient of variation of the variables simulated at x in i by the TRMM/WFD (P) and of the observed precipitations (P_{obs}).

4.3 Optimization rain gauge network using Posteriori Method

Using the Posteriori Method to investigate the density and location of rain gauges on the discharge simulation in hydrologic models, various scenarios of different rain gauge densities are built based on the rain gauge networks that stochastically resampled. First, given a series of certain numbers of gauges that the rain gauge networks should contain to build the scenarios (e.g. the resampled rain gauge networks comprising of 5%, 10% and 20%, etc. of the total number of rain gauge from the benchmark rain gauge network). Then, for each scenario, a given number (i.e. 100 in Paper II and 5000 for Paper III) of different rain gauge network configurations composing of randomly selected rain gauges from the benchmark network are derived.

4.4 Optimization rain gauge network using Transcendental Method

The rain gauge network optimization using Transcendental Method is based on the entropy theory by applying the multi-criteria algorithm.

4.4.1 Shannon's entropy and Mutual Information

Shannon's Entropy (*H*) (1949) is a measure of the uncertainty in a random variable (Ihara, 1993), which quantifies the expected value of the information contained in a message. Information Entropy is the average unpredictability in a random variable, which is equivalent to its information content. Mathematically, the amount of information is inversely related to the probability of occurrence. Mutual information of two random variables is a quantity that measures the mutual dependence of the two random variables (Steuer et al., 2002). In our case the two random variables are two rain gauges *X* and *Y*. The precipitation information of rain gauges *X* and *Y* may overlapping. To find out the amount of mutual (overlapped) information of the two rain gauges, transferable information computation can be applied which similar to using the *X* rain gauge to forecast *Y*'s information. The reduction in information about one variable due to knowledge of the other is mutual information of rain gauges *X* and *Y*.

4.4.2 Rain gauge network optimization

To find the optimal rain gauge network with different number of rain gauges, various scenarios of different rain gauge densities were built. The best and good rain gauge networks are selected from 5000 different network configurations composing of Monte Carlo stochastically selected rain gauges from the benchmark rain gauge network via the following steps:

(1) Compute the Shannon's Entropy (*H*) of each rain gauge and find the rain gauge with maximum H_{max}. Then adopt Monte Carlo stochastic selection method to composite the feasible rain gauge network set Θ' which includes 5000 different combinations of each given gauge number (*d*) from the surplus 184 rain gauges (except the rain gauge H_{max}). Then add the rain gauge of maximum entropy into each rain gauge network in Θ' to composite the rain gauge network set Θ.

(2) To find the "best" network configuration in a given number of rain gauges, a multi-criteria algorithm was applied based on values computed for three objective functions (OFs) in dataset Θ.

$$\begin{cases} F_1(\theta) = \bar{I} = \dfrac{\sum_{i=1}^{d-1}\sum_{j=i+1}^{d} I(X^i, X^j)}{C_d^2} \\ F_2(\theta) = PBIAS = \dfrac{\sum_{t=1}^{n} \left|(x_t - p_t)\right|}{\sum_{t=1}^{n} p_t} \\ F_3(\theta) = E_{ns} = 1 - \dfrac{\sum_{t=1}^{n}(x_t - p_t)^2}{\sum_{t=1}^{n}(p_t - \bar{p})^2} \end{cases} \tag{6}$$

Where X^i and X^j are rain gauges pair derived from Θ, C_d^2 is the combinatorial number equals to $\frac{d\times(d-1)}{2}$. p_t is the "true" areal mean precipitation (computed by using all the 185 rain gauges in the catchment) at time interval t, x_t is the sampled areal mean precipitation from a given network configuration at that time interval, and n is the number of 1 day time intervals analysed. The over score operator (as in $\bar{x}$ and $\bar{p}$) indicates the average of the measure (p_t) over all n time intervals considered. $F_1(\theta)$ is the arithmetic mean of the mutual information computed by all bi-combinations of the rain gauges (X^i and X^j) from Θ which represents the rainfall information "overlapped" among gauges. $F_2(\theta)$ is *PBIAS* which measures errors in global rainfall volume input to the catchment, computed as the absolute residual percent bias. $F_3(\theta)$ is the Nash-Sutcliffe Coefficient (E_{ns}) which determines the relative magnitude of the residual variance ("noise") compared to the measured data variance ("information") (Nash and Sutcliffe, 1970).

(3) Using the multi-criteria optimization algorithm to find rain gauge networks that optimize all OFs simultaneously from Θ. Due to multi-criteria optimization problem has a set of solutions but not a unique solution that simultaneously optimizes each criterion, it is necessary to take use a Pareto set of solutions which have the property that moving from one solution to another will result in the improvement of at least one criterion while causing deterioration in at least one other (Jayawardena, 2014). However, the rain gauge network design needs a unique solution in practise, while it is difficult to identify any of the Pareto solutions as being objectively better than any of the other Pareto solutions before validated in hydrological models; the identification of a restricted set of Pareto solutions allows for the subjective selection of an appropriate single network can be referred as "compromise solutions". The compromise solution fulfils the multiple-criteria requirements for an appropriate final "best" network. Therefore, the final "best" network selected by the Pareto solution which corresponds to the most favourable compromise between the

three OFs is the solution for which each objective function has been optimized to the extent that only minor improvements are traded off for a stronger deterioration of at least one other objective if it can be optimized any further. After selecting the best rain gauge network, all solutions close to the Pareto front (i.e. $\overline{I}$ =*min*($\overline{I}$), *PBIAS*=0 and *NSC*=1) in proximity to this best solution may be of interest as they represent as "good" rain gauge networks that are similar with respect to their compromise between the three OFs.

5 Results

5.1 Paper I

The comparison of global grid datasets (TRMM and WFD) and evaluation of the datasets in hydrological modelling in Xiangjiang River basin, south China reveal obvious differences in the statistical indices and hydrological model performances among the datasets. The main findings from the study are:

(1) The differences of the mean annual and seasonal areal precipitation calculated from the gauged precipitation and the two original global datasets (TRMMo and WFDo) are in general within the acceptable value of less than 10%, and the linear correlation between the monthly gauged precipitation and TRMMo and WFDo data as reflected by the interception, slope and R^2 are in general very good. However, the spatial differences as reflected by the results of Kolmogorov-Smirnov test and F-test on each grid for distribution pattern and variance are found to be significant between the gauged and the two global datasets (TRMMo and WFDo) in most grids, while the mean values are tested by the Student's t-test shows that two thirds (one third) of the grids of $TRMM_O$ (WFDo) rainfall in the basin are not significantly different with the gauged rainfall on the 5% significance level.

(2) The bias correction methods are able to remove the biases from the mean values of TRMMo and WFDo datasets. The nonlinear bias correction method gives good results in correcting the standard deviation values in TRMM/WFD data at grid level. The E_{ns} values of TRMM data improved after nonlinear bias correction in most of the grids as well as in the areal mean rainfall. The linear bias correction method gives good results in correcting the standard deviation of areal mean WFD data. But the E_{ns} values of WFD data do not improve in both grid and areal mean level after linear or nonlinear bias correction.

(3) The comparison of model simulation results using gauged precipitation and the two original global datasets (TRMMo and WFDo) as inputs to the two hydrological

models reveals that at daily time step observed precipitation data produce much better results than both TRMMo and WFDo in terms of Nash-Sutcliffe efficiency E_{ns} and relative error, R_E. Both linearly and nonlinearly bias corrected TRMM and WED data do not significantly improve the model simulation results at daily time step. While at monthly time step, modelling results show that both TRMM and WFD data produce acceptable model simulation results in terms of both Nash-Sutcliffe efficiency (E_{ns}>0.7 for original and nonlinear corrected TRMM/WFD data, E_{ns}>0.8 for linear corrected TRMM/WFD data) and relative error (all $|R_E|$<10%).

5.2 Paper II

The investigation of the characteristics of the mean areal rainfall estimated by different rain gauge densities and their influence on the performance of the Xinanjiang model in Xiangjiang River Basin mainly reveals the following results:

(1) The slight change of median value of mean areal rainfall from different rain gauge networks demonstrates that the 100-time random selection for each number of rain gauges is enough to represent different variation cases of areal rainfall. The comparison of the observed mean areal rainfall from all available rain gauges show that relative errors of the mean areal rainfall estimated from fewer rain gauges increased as the number of selected rain gauges decreased.

(2) Acceptable model performance is achieved when the number of rain gauges ranged between 93 and 128 irrespective of the gauge configurations. However, the probability of getting poor model performance is very much increased when the number of rain gauges falls below 38.

(v) The correlation coefficient between the areal mean rainfalls calculated by 181 stations and by fewer rain gauges ($\rho_{r\text{-}r}$), and the correlation coefficient between the observed runoff and the simulated runoff with the input of different rain gauge densities ($\rho_{f\text{-}f}$) increase hyperbolically in the same step with the increase of the number of rain gauges. However, after the threshold of 93 rain gauges, both $\rho_{r\text{–}r}$ and $\rho_{f\text{–}f}$ suggest no change.

(vi) Better model performance can be achieved with fewer rain gauges if an optimum spatial configuration is provided and is determined by considering the mountain areas where heavy orographic rainfall is the dominant pattern of the local precipitation.

5.3 Paper III

This paper designs an entropy theory based multi-criteria rain gauge network resample method to investigate the influences of the optimised gauge networks with varying rain gauge densities and gauge locations on lumped and distributed hydrological models. Several aspects of the results in the study reveal that the rain gauge networks selected by this method are robust and optimal. It is concluded from the study that:

(1) There is no significant difference between the annual areal mean rainfall estimated by the optimal (best and good) rain gauge networks with different densities and the benchmark network (185 gauges), although the spatial distribution patterns change with the number of stations and the location of the stations. This is the main reason why the performance of the lumped Xinanjiang model does not change much with the number of rain gauge used but the distributed SWAT model does. Meanwhile, the effect of the increase in the number of rain gauges in optimized networks on the variance reduction of mean areal precipitation is not obvious.

(2) The best and good rain gauge networks based on the lumped Xinanjiang Model give small relative errors (all $|R_E|<2\%$) and high values of Nash-Sutcliffe model efficiency coefficient (all $E_{ns}>0.92$) in the calibration period, no matter how many rain gauges are included in the optimized networks; while in validation period, the relative errors ($-8\%<R_E<3\%$) are slightly increased and the values of E_{ns} (>0.89) are

slightly decreased when using the good networks with only nine rain gauges in the simulation.

(3) In general, the performance of the distributed SWAT Model is somehow lower than the lumped Xinanjiang Model, and also larger variability can be observed in simulated runoff using optimized networks with varying rain gauge densities. The relative errors are -6%~9% and -7%~14% for the calibration and validation periods respectively. Meanwhile, a clear improving trend can be observed in the values of E_{ns} with more rain gauges included in the optimized networks in hydrological modelling.

6 Conclusions

In this thesis, characteristics of the impact of the spatial resolution of precipitation data from various sources (global grid data—TRMM and WFD and resampled rain gauge network data) on hydrological modelling were investigated. For the evaluation of (1) hydrological modelling using original and bias adjusted TRMM and WFD datasets, (2) hydrological modelling using stochastically resampled rain gauge networks, and (3) hydrological modelling using Transcendental Method resampled rain gauge networks, considerable differences of model performances were observed due to the variation of the precipitation data input into the hydrological models. The following are the key conclusions:

(1) As shown in paper I, the daily step hydrological simulation using global gridded data (TRMM 3B42 and WFD) gave unsatisfactory model performances; while the bias adjusted global grid data meet the requirements of hydrological modelling to some extent. Therefore, compared with the indirect source of precipitation information (global grid data), the precipitation derived from rain gauge networks with proper gauge density and location is the first choice for hydrological modelling.

(2) Under the limitation of rain gauge density, the rain gauge location plays a vital role in determining the performances of hydrological modelling; especially when applied in the distributed hydrological model simulations. The stochastically designed rain gauge networks produce obvious uncertainty in streamflow simulation, while the resampled rain gauge networks using entropy based multi-criteria method produce stable performances when using the lumped Xinanjiang Model and a bit larger uncertainties were observed in streamflow simulation using the distributed SWAT Model. The results demonstrate that the distributed hydrological model is very sensitive to both rain gauge location and density.

(3) The study provides theoretical based and practical information in rain gauge network design. In areas with approximately homogenously distributed precipitation, the placement of rain gauges should be evenly distributed over the entire catchment

whereas more rain gauges should be emplaced in the mountain area where the precipitation show obvious variation for areas with heterogeneous spatial precipitation distribution.

Throughout the study, it has been observed that since hydrological models are systems with highly nonlinear input-output relations, the precipitation data input with insignificant statistical differences can nevertheless produce significant differences of simulated streamflows in hydrological modelling. The thesis therefore contributes to the understanding of discharge simulations using precipitation from different sources. Furthermore, resampling of the rain gauge network using the Transcendental Method and Posteriori Method provides examples with reference value for investigating the relationship between the input and output in hydrological modelling and the thesis contributes to the informativeness and applicability of this study field.

Overall, the results of the present study as well as recent research on the influence of the precipitation data in hydrological modelling suggest a promising area for future research. The results are valuable, for instance, for hydrological modelling using multiple sources of precipitation data and for designing rain gauge network in poorly gauged areas. The results of this study indicated that precipitation is of vital importance in regional hydrological study and will provide useful guidelines and valuable reference for studying rainfall influence in hydrological modelling and water resources management.

Further investigations and developments of the study on the impact of precipitation data on hydrological modelling may include:

(1) Compare different bias correction methods and design new algorithms to correct the bias of global grid precipitation data based on the gauged data and compare the bias corrected global grid datasets in hydrological modelling, especially in testing the suitability of these data in distributed hydrological models.

(2) This study was conducted based on the existing densely distributed rain gauge network; however, discharge modelling in ungauged basins is still a challenge for hydrologists, hence use of satellite or radar precipitation data in designing rain gauge networks need to be further investigated.

(3) This study mainly considering the impact of precipitation on hydrological modelling. However, the input of the entire meteorological datasets also plays an important role in hydrological modelling. The uncertainties of the entire meteorological datasets on hydrological models should therefore also be given attention in the future studies.

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Figures

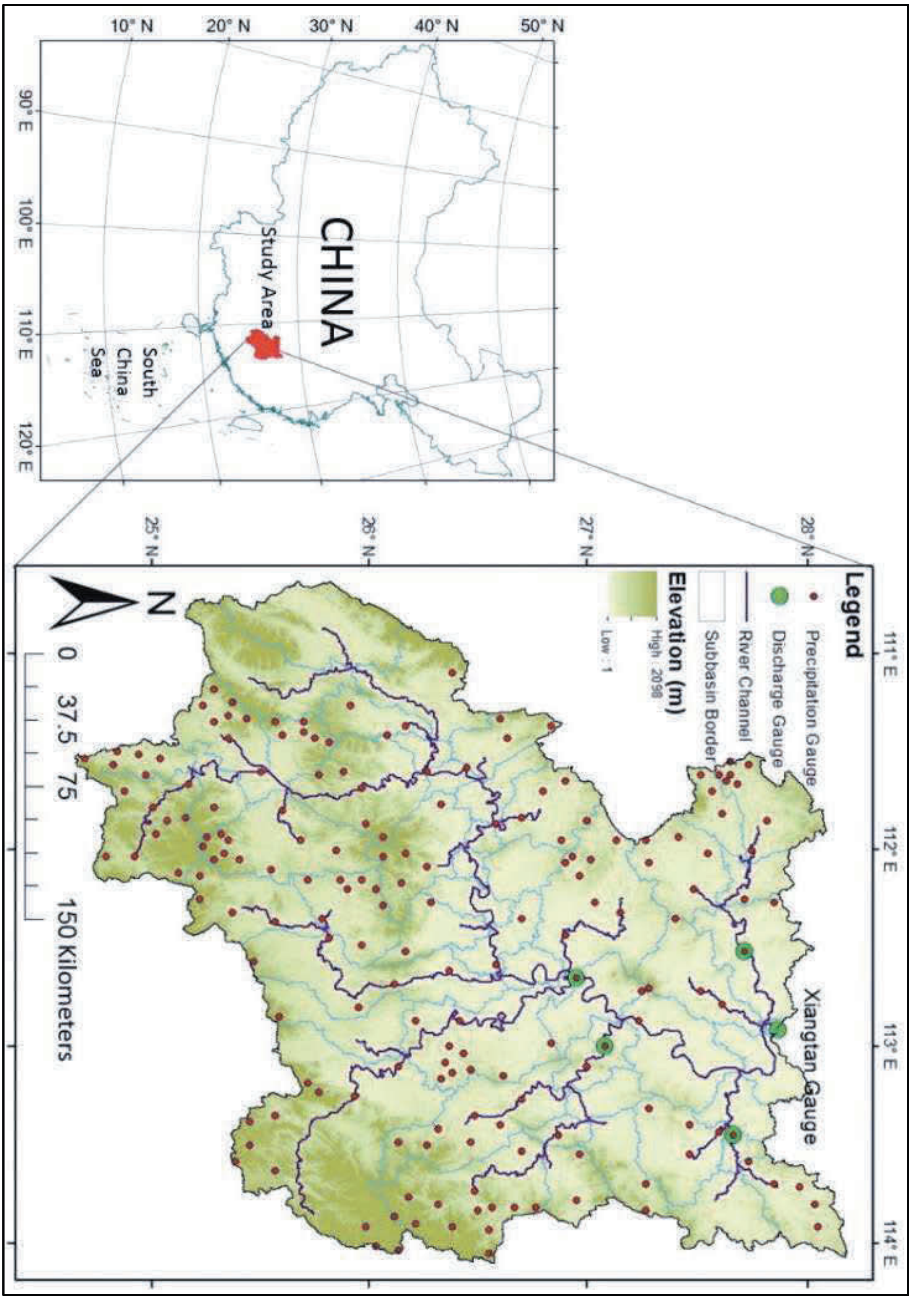

Figure 1. The study area of Xiangjiang River basin

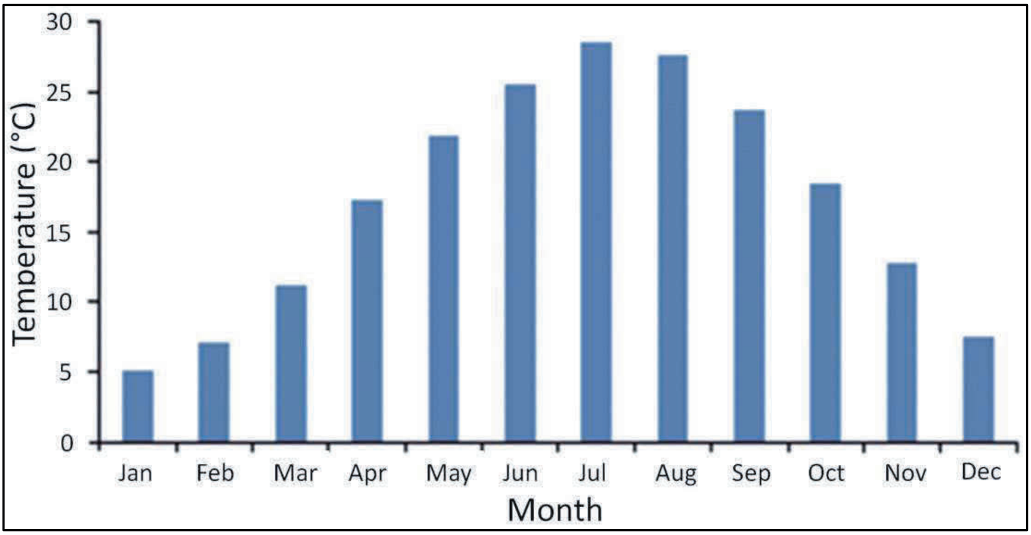

Figure 2. The mean monthly temperature in Xiangjiang River basin

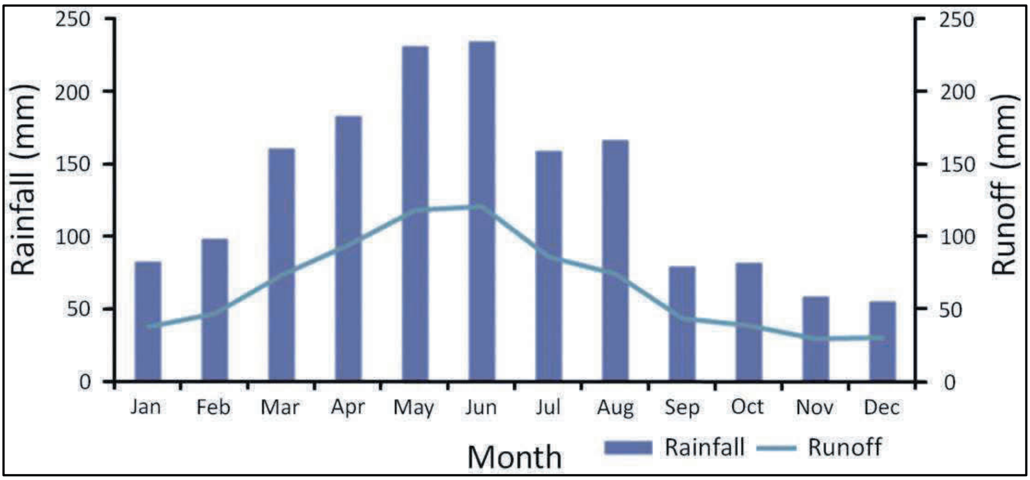

Figure 3. The mean monthly rainfall and surface runoff in Xiangjiang River basin

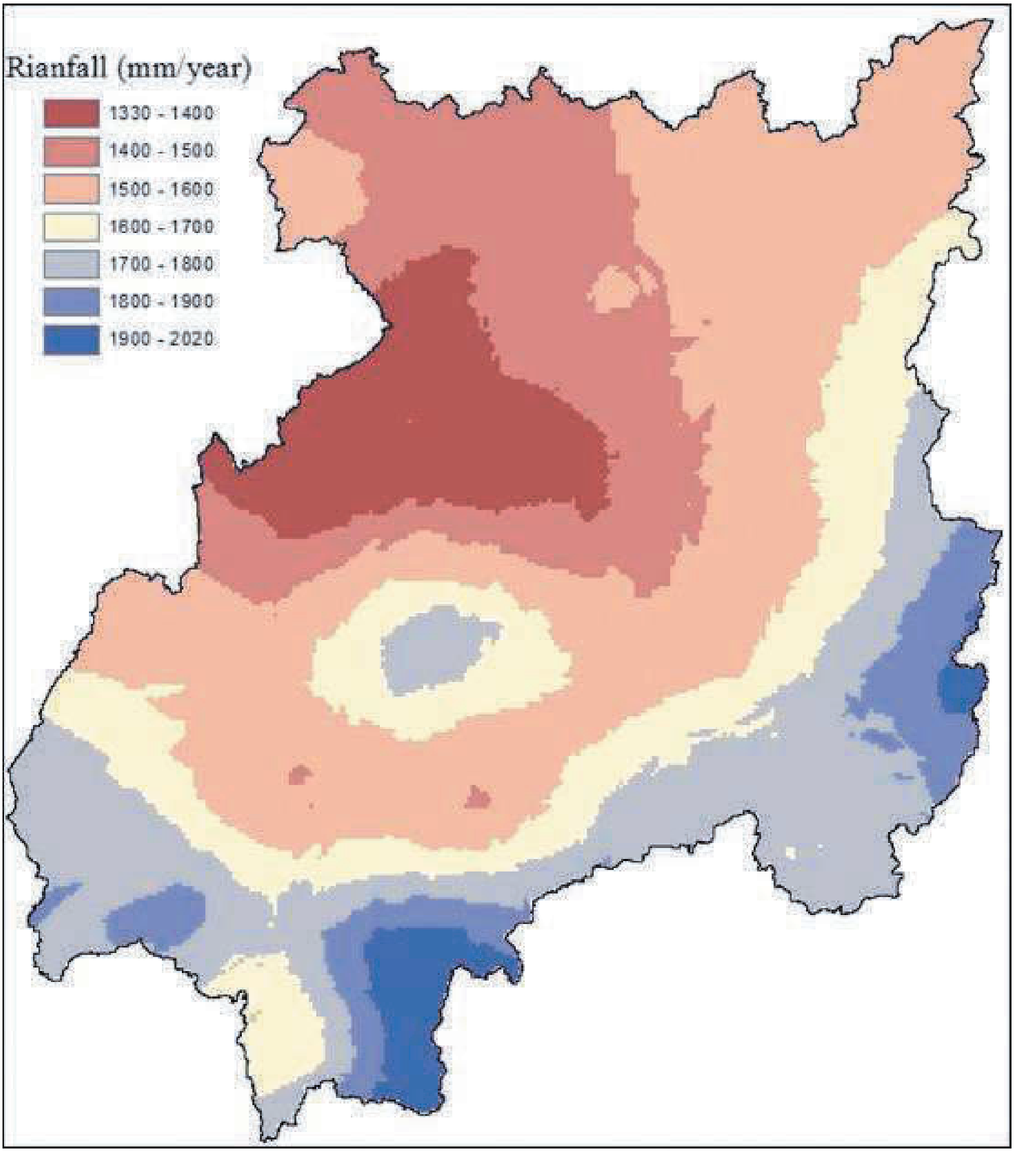

Figure 4. The distribution of annual mean rainfall over Xiangjiang River basin

Tables

Table 1. The calibrated parameters of Xinanjiang Model

Parameter Name	Description	Parameter Range
U_m	Averaged soil moisture storage capacity of the upper layer (mm)	10~60
L_m	Averaged soil moisture storage capacity of the lower layer (mm)	50~160
D_m	Averaged soil moisture storage capacity of the deep layer (mm)	100~180
B	Exponential parameter with a single parabolic curve, which represents the non-uniformity of the spatial distribution of the soil moisture storage capacity over the catchment	0.3~0.7
I_m	Percentage of impervious and saturated areas in the catchment	0~0.1
K	Ratio of potential evapotranspiration to pan evaporation	0.1~1.2
C	Coefficient of the deep layer that depends on the proportion of the basin area covered by vegetation with deep roots	0.1~0.3
S_m	Areal mean free water capacity of the surface soil layer, which represents the maximum possible deficit of free water storage (mm)	30~60
E_x	Exponent of the free water capacity curve influencing the development of the saturated area	1~2
K_g	Outflow coefficients of the free water storage to groundwater relationships	0.9~0.99
K_i	Outflow coefficients of the free water storage to interflow relationships	0.8~0.9
C_g	Recession constants of the groundwater storage	0.3~0.7
C_i	Recession constants of the lower interflow storage	0.3~0.7
K_e	Parameter of the Muskingum method	0.1~4
X_e	Parameter of the Muskingum method	0.1~4

Table 2. The calibrated parameters of SWAT Model

Parameter Name	Description	Parameter Range
ALPHA_BF	Base flow recession factor (days)	0~1
GW_DELAY	Ground water delay (days)	0~15
GW_REVAP	Ground water revaporation coefficient	0~0.5
GWQMN	Threshold depth for ground water flow to occur (mm)	0~10
SLSUBBSN	Average slope length (m)	0~100
SOL_BD	Moist bulk density (g/cm^3)	0~25
SOL_K	Saturated hydraulic conductivity (mm/hour)	0~10
REVAPMN	Threshold depth for revaporation to occur (mm)	0~100
ESCO	Soil evaporation compensation factor	0~1
SOL_AWC	Available water capacity (m/m)	0~1
CN2	Curve Number	-25~30
SURLAG	Surface runoff lag coefficient (days)	0~20