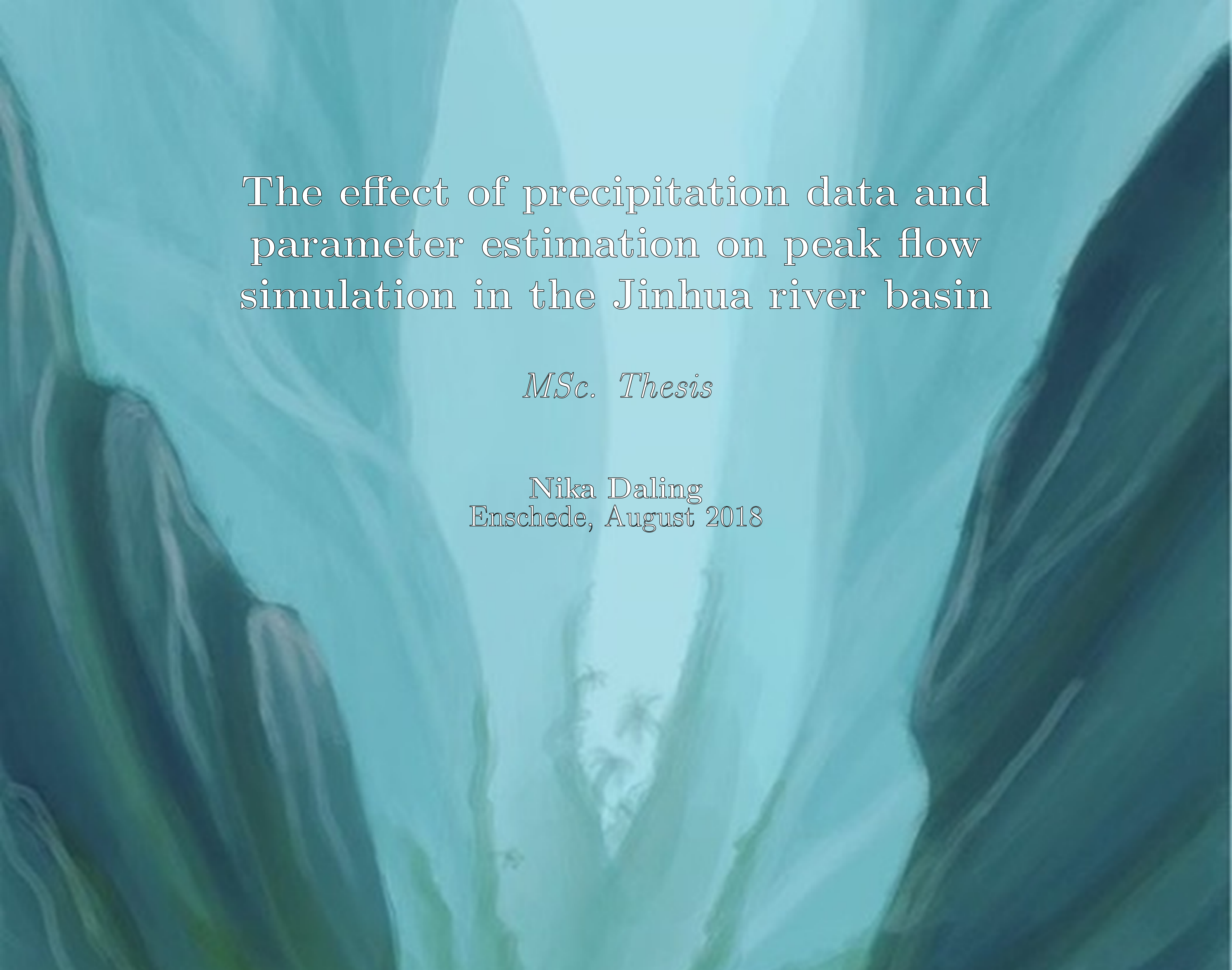

The effect of precipitation data and parameter estimation on peak flow simulation in the Jinhua river basin

MSc. Thesis

Nika Daling
Enschede, August 2018

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Water Engineering and Management

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Illustration on cover: Palm tree valley. By Dian Karssen (2018)

Preface

This document contains the report of the MSc. graduation research that was done to improve the simulation of peak flows in the Jinhua river basin.

This report marks the end of my master and career as a student at the University of Twente. In this study I have looked into the effects of precipitation and parameter estimation on peak discharges in the Jinhua river basin using DHSVM. For this I got the opportunity to visit China and perform part of my research at the Zhejiang University.

I would like to thank all the wonderful people I met at the Zhejiang University for the warm welcome I received, making me feel at home and taking me around Hangzhou. A special thanks goes to Suli Pan and Zhixu Bai for helping me with everything I needed to make the model work and helping me preparing the data that I needed. Also, my gratitude goes out to Yueping Xu, my supervisor at the Zhejiang University, by whom I could always knock on the door for questions and feedback.

To Martijn Booij and Tom Rientjes, thank you for the always quick and adequate feedback and advise that I received via mail during my stay in Hangzhou and for the help I received in the start up phase of the research and during finalisation of this report when I got home.

Finally I want to thank all the people I have met and stood beside me in the six years that I had the pleasure to study in Enschede. Especially to my family and boyfriend from whom I received nothing but the greatest support and love in all the decisions that I made.

Nika Daling
Enschede, June 2018

Summary

Precipitation is the main driving force of the generation of run off. It is therefore an important model input for hydrological models. However, precipitation is highly variable in space and time and is hard to measure at an appropriate resolution. A number of studies have been done to find how precipitation affects the discharge generation. The effect on peak discharges is however less known, even though the correct modelling of flood peaks in general is desired for disaster prediction and prevention and sustainable river management. Therefore this study focuses on using precipitation data in the simulation of peak discharges. To perform this study a case study is set up using the Distributed Hydrology-Soil-Vegetation Model (DHSVM) in the Jinhua river basin, East China. For this study the precipitation data is obtained from two overlapping networks of 5 and 21 stations respectively throughout the entire river basin. It is assumed that the dense network provides improved rainfall representation and improves the peak discharge simulation. An important element in this study has been the estimation of parameters to calibrate the model against measured discharge data.

This study was divided into two parts. First the effects of the precipitation and parameter estimation were investigated. For this the entire discharge series is used as well as a shortened time series that only included the individual peak flows. In the second part of the research an attempt has been made to improve the model performance, based on the results from the first part of the research. The first focus was on how the precipitation affects the peak discharge and what still can be done to improve the model by correcting the precipitation data for various measurement errors. It has become clear that the precipitation data that is currently used has been cleared of measurement errors due to failure of equipment. Also, the model already corrects for height when interpolating the precipitation. However, structural errors in the measurements such as wind induced errors and, wetting and evaporation loss are not corrected for. After this the relation between precipitation and (peak) discharges was examined through a sensitivity analysis. It was found that precipitation correlates with discharge in a non linear way and the precipitation and the peak discharges are correlated as well. It was concluded that the precipitation has a significant influence on peak discharge simulation and it is worthwhile to use this as a way to improve the model performance in the second part of the research.

Secondly a small sensitivity analysis was performed to investigate the effect of the parameter estimation on the discharge simulation and model performance for the entire discharge time series and peak discharges. For this sensitivity analysis a univariate approach was chosen using the range based on a previous study. The parameters that were looked into were chosen based on the parameters that the discharge simulation in DHSVM was found to be sensitive to according to a previous study in the Jinhua river basin. As expected it was found that the parameter estimation indeed has an influence on the peak discharge simulation. The parameters, however, influence the peak discharge simulation in a lesser extent than the precipitation did. The parameters that influenced the (peak) discharge simulation most are the porosity (ϕ), the field capacity (θ_{fc}), the wilting point (θ_{wp}) and the lateral conductivity (K) of clay loam soil, and the rain LAI multiplier (Rj).

Next, an attempt has been made to improve the model performance, with a focus on the peak discharges. This was done in three steps, namely the correction of structural measurement errors in the precipitation data, the implementation of additional gauge stations and the optimisation of the model parameters. The removal of the structural measurement errors had an effect on the simulated discharges, and with respect to the peak discharges the model performance improved. However, for the entire discharge series the model performance decreased. The

increased density of the precipitation data was more difficult to examine, due to the decreased time period. This because of the limited amount of available data from the additional stations and missing observed discharges after 2008. After the implementation of the 16 additional stations the model performance was assessed again. The hydrographs also have been analysed visually. The model performance for the 21 stations did not improve greatly over the entire discharge and even decreased drastically when focussing on the peak discharges compared to the situation with five meteorological stations. Therefore the choice was made to perform a calibration procedure using the automatic genetic calibration algorithm ε-NSGA-II with three objectives: the Nash Sutcliffe coefficient, PBIAS and Mean fourth power error. These are all statistical functions that indicate the similarity between the observed and simulated discharges. The five parameters that were found to affect the peak discharges most were used as calibration parameter. This was done for the situation with corrected precipitation with 21 stations as well as 5 stations to make the results more comparable, since a new objective has been added. The available data was split into two periods in such a way that for calibration 1.25 year was available and 1 year of data was used for validation. After the calibration it turned out that for both situations the model's performance increased drastically compared to the initial state of the model in the calibration period. However, the model with 21 meteorological stations only showed slightly better results to the one with 5 meteorological stations. The improvement here was only visible in the PBIAS value during this period, the NS coefficient was constant for the entire discharge series as well as for the peak discharges. This indicated an improvement in the base flows, instead of the peak flows. For the validation period the model performance increased slightly for the two calibrated models compared to the initial state of the model. The model performance did not improve when comparing the model with 21 stations to the model with 5 stations, it even declined.

It was believed that 16 additional stations would increase correctness of rainfall representation enough to be able to capture the spatial variability better. However, in the model with 21 stations the total annual precipitation in the area decreased, causing lower peak flows. The precipitation station that are used in this study are all located at the lower elevations of the study area near river branches. To get a better rainfall representation the response of the precipitation to an increase in elevation should be further examined, since this is not known in this study area. For the improvement of the model there can still much be won by for example investing in gauge stations at higher elevations. In general it can be concluded that the increase in gauge density does not necessarily improve the peak discharge simulation.

For further research on this subject the sensitivity analysis performed in this study can be extended, since it was based on an earlier study that focussed on the entire discharge series using a two-step sensitivity analysis. However, it is possible that the peak discharges respond more strongly to other parameters that were not included in the sensitivity analysis performed in this study. Also, the model was calibrated and validated with a limited time period. There is more observed data available at the meteorological bureau, however it was not accessible during this study. If the additional observed discharges would be accessible for future research the calibration and validation of the model could be done more extensively which would help with improving the peak discharge simulation and also the analysis of the model performance with regard to the peak flows. Finally, other discharge stations in the study area can be used to see whether the underestimation of peak discharges is a problem in the entire catchment or only at the Jinhua outlet.

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1 Introduction

Precipitation is the main driving force of the generation of run off (Sorooshian et al., 2011). It is therefore an important model input for hydrological models. However, precipitation is highly variable in space and time and is hard to measure at an appropriate resolution. A number of studies have been done to find how precipitation affects the discharge generation. The effect of precipitation on peak discharges is however less known. Peak discharges are an important phenomenon, since they can cause large flood events. Therefore, the improvement of modelling flood peaks is desired for disaster prediction and prevention, and sustainable river management (Pan et al., 2017). Especially in precipitation driven rivers that are located in areas where there is an uneven distribution of precipitation, the discharges can vary greatly throughout the year. The Jinhua river basin, East China, is such an area where the precipitation distribution is unevenly in time and will therefore be used in this study as a case study how peak discharges can be simulated more accurately. Also in previous studies in the Jinhua river basin it was found that peak discharges are underestimated (Xu et al., 2014; Pan et al., 2017), so there is a potential to improve this during this study.

Many hydrological models have been developed, all with different characteristics that are more or less suitable, depending on the goals one has using the model. In this research a physics based, distributed model will be used to model the run off in the Jinhua river basin. The Distributed Hydrology-Soil-Vegetation Model (DHSVM), developed by Wigmosta, Vail, and Lettenmaier (1994) and further extended by Wigmosta, Nijssen, and Storck (2002), will be used in this study. The choice for DHSVM was mainly made because this model has been used in this study area in previous researches (Xu et al., 2014; Pan et al., 2017). Currently, the model runs with a spatial resolution of 200x200 meter and a temporal resolution of one day and uses precipitation data gathered from five meteorological stations spread across the Jinhua river basin. This model has been used in earlier studies (Pan et al., 2017; Xu et al., 2014), in which it was concluded that the model underestimates the peak flows, which is known behaviour for DHSVM (Safeeq and Fares, 2012). The main reason for using the model is that in earlier studies the model has already been successfully used and calibrated for the catchment area that is focussed on in this study for a spatial and temporal resolution of 200 meter and daily respectively (Xu et al., 2014; Pan et al., 2017). Y. Xu (personal communication, January 24, 2018) stated that the initial reasons for choosing DHSVM were that (1) the model is a sub-daily, fully distributed hydrological model, (2) the model had already been successfully used by meteorological colleagues in the study area, (3) the model performs well on modelling floods and it can be used for investigating the role of roads on the discharge, and finally (4) the model has an urban module which can model the urbanised catchment in a simple way. However, Y. Xu (personal communication, January 24, 2018) also found that the model is not an easy model to use, which is a known disadvantage for distributed models (Liddament et al., 1981).

This chapter will first provide the state-of-the-art literature review in Section 1.1. From this the research gap, objective and relevance of this research are stated in Sections 1.2 and 1.3. This will also contain the research questions that are phrased for this research. This chapter will end with the further outline of this thesis in Section 1.4.

1.1 State-of-the-art literature review

In the course of time numerous hydrological models have been developed to model run off flows. The development resulted in a higher demand on data, and the choice of the appropriate model in a research has become more difficult (Todini, 2007). Classifications of models have been made by several researchers, including Pechlivanidis et al. (2011), who classified the models based on model input and the extent of physical principles applied. Pechlivanidis et al. (2011) describes three types of models: empirical, conceptual and physics based models. Each of these models have their advantages and disadvantages. Empirical models are the most simplistic of the three, which makes the implementation relatively easy (Pechlivanidis et al., 2011). Conceptual models contain in general all the components of hydrological modelling that are found of importance at the catchment scale, although the complexity of conceptual models varies considerably (Pechlivanidis et al., 2011). According to Wheater (2002), it is of importance to find a good balance between model complexity and good run off prediction, since data is not always available to support more complex models. Pechlivanidis et al. (2011) finally describes physically-based models, which are defined by measurable parameters and can provide continuous simulation of the run off. These models are, however, based on small scale in-situ measurements or laboratory data, which makes their applicability to larger areas questionable. Also the computational burden makes these models less useful than more simplistic models.

The model that will be used in this research is DHSVM, which is a distributed, physically based model, developed by Wigmosta, Vail, and Lettenmaier (1994) and has been extended and improved by Wigmosta, Nijssen, and Storck (2002). Xu et al. (2014) and Pan et al. (2017) found that DHSVM underestimated the peak flows in the Jinhua river basin, which has also been the case in other studies using DHSVM (Safeeq and Fares, 2012). A more detailed description of the model and the study area can be found in Chapter 2.

In a study by Tian et al. (2014) three conceptual models (GR4J, HBV and Xinanjiang) were used to model the run off in the Jinhua river basin. The performance of these models has been evaluated using the Nash Sutcliffe coefficient. This is a normalised statistic that determines the relative magnitude of the residual variance compared to the measured data variance (Nash and Sutcliffe, 1970). The value of the NS can be between -∞ and 1, where 1 corresponds to a perfect accuracy of the model. The models in the study by Tian et al. (2014) too underestimated the run off, however their performance was better than that for DHSVM as can be seen in Table 1. Nonetheless, the Nash Sutcliffe coefficient value for DHSVM does exceed the value for what is considered a good model performance.

Table 1: Model performance expressed in Nash Sutcliffe coefficient for four different types of models (Tian et al., 2014; Xu et al., 2014)

	GR4J	HBV	Xinanjiang	DHSVM
Calibration	0.91	0.91	0.88	0.73
Validation	0.93	0.91	0.89	0.70

One of the most important input data when performing a hydrological study is precipitation (Barros et al., 2008; Sorooshian et al., 2011; Syafrina et al., 2014). Good data quality, that is representative for the entire study area, is therefore of importance. Zhu et al. (2016) describe the difficulty of correctly measuring precipitation, due to its high spatial and temporal variability. There are different ways of obtaining data: (1) ground-based measurement networks, (2) satellite products and, (3) stochastic precipitation models. Rain gauges are the oldest way of obtaining precipitation data, however they are often widely spread in space, which makes the capturing of spatial variability not adequate (Miao et al., 2015). According to Müller (2011) rain gauges' advantages are that they can measure precipitation at a fine temporal scale, and they measure the precipitation directly (Germann et al., 2006). Another ground-based way of measuring is through radar, which can monitor a larger area on a high resolution, but the data it produces is not directly usable (Germann et al., 2006; Müller, 2011). The use of satellite-derived precipitation estimates started in the 1970's and have provided useful weather information, which gave the possibility to assess precipitation properties at a large scale on a sub-daily basis (Haile et al., 2012; Sorooshian et al., 2011). Multiple studies have been done on the accuracy of rainfall products produced by satellite, for example by Zhu et al. (2016) and Haile et al. (2012). From these two studies can be concluded that CMORPH performed the best, although the differences between all the satellite products were small. Finally, stochastic precipitation models, also known as weather generators, are discussed. These models generally consist of two components, one generates the precipitation occurrence and one simulates the precipitation amounts (Ng et al., 2017). Weather generators have the ability to overcome the limitations of measuring precipitation data, however it is necessary to calibrate and validate them for a new region to ensure their applicability (Ng et al., 2017). This research focusses on the increase of rain gauge stations to improve the model, since these are available in the area.

The current model that is used in the Jinhua river basin is calibrated and validated for a spatial resolution of 200x200 meter and a temporal resolution of one day. In an ideal situation the precipitation input data would be of the same resolution, or smaller (Blöschl and Sivapalan, 1995). However, this is not the case for the spatial resolution. Therefore the precipitation data needs to be interpolated and extrapolated to match the spatial resolution of the model.

1.2 Research gap

In previous research a model in DHSVM was set up for the Jinhua river basin, but even though the Nash Sutcliffe coefficient indicated a good model performance, it was still visible that the peak flows were underestimated. The current precipitation data is gathered from five meteorological stations throughout the Jinhua catchment. This data has a coarse resolution, which may be the cause of the underestimation of the peak flows. In this catchment area, there has not been a study with other data than that obtained from the five meteorological stations. It is thus not known what the influence is of rainfall representation by use of a more dense rain gauge network in the Jinhua river basin.

Besides the data that is used in the model, the parameter estimation has an important role in the discharge simulation. DHSVM consists of many parameters that can be used for calibration. This makes it hard to fully calibrate the model, especially combined with the calculation time the model requires. Xu et al. (2014) calibrated the model using a trial-and-error method. After this Pan et al. (2017) did a sensitivity analysis to parameters in the Jinhua river basin that the model is sensitive to and recommended in future research to focus on calibrating with these parameters. The sensitivity analysis done by Pan et al. (2017) was performed for the entire discharge series, however the effect of parameters on peak discharges using DHSVM has not been researched yet in the Jinhua river basin.

1.3 Objective and research questions

Precipitation is the main driving force in the generation of run off (Sorooshian et al., 2011) and also the parameter set of models can have an effect on this. In previous research it was noted that for the Jinhua river basin the peak discharges are underestimated. There has not been a study to the peak discharges in this basin. The objective of this research is therefore:

Finding the effect of precipitation data and parameter estimation on simulated peak discharges and trying to improve the peak flow simulation in the Jinhua river basin using DHSVM.

1.3.1 Research questions

Three research questions have been formulated to achieve the research goal:

1. How is the currently used precipitation data treated and what is the effect of precipitation data on peak flow simulation?
2. What is the effect of parameter estimation on peak flow simulation?
3. How can the current model predictions be improved with regard to peak flows using precipitation data and parameter estimation?

1.4 Outline

This report will go into detail about the research that has been performed. First the used model and data will be further elaborated on in Chapter 2. Also the study area that has been focussed on will be further introduced in this chapter. In Chapter 3 the method how the research questions were answered is given. After this Chapter 4 will give the results of the research questions. This document will end with a discussion, conclusion and recommendations in Chapters 5 and 6.

2 Study area, model and data

This chapter elaborates on the study area where the study has been performed, the model and the optimisation code that have been used during this study in Sections 2.1 to 2.3. Also the used data and how it was obtained is discussed here in Section 2.4.

2.1 Study area

This study focusses on the modelling of the peak discharge in the Jinhua river basin, located in the Midwest of the Zhejiang Province (East China). The river is a tributary of the Qiantang river and has a length of 195 km and the catchment area of the river is 6785 km^2 (Pan et al., 2017). For this study the area upstream of the Jinhua discharge station will be used, which has a total area of 5996 km^2 (see Figure 1). The elevation of the river basin varies from 29 to 1296 m above mean sea level. The Jinhua River is rainfall dominated and is located in an area where the predominant climate is Asian subtropical monsoon. This is characterised by hot, wet summers and cold, dry winters. The annual average precipitation and temperature in the area are 1424 mm/year and 17 °C, respectively. Due to the climate more than 50% of the annual precipitation falls in the period May to July. This uneven temporal distribution of precipitation is the cause that the Jinhua River Basin experiences droughts and floods (Pan et al., 2017).

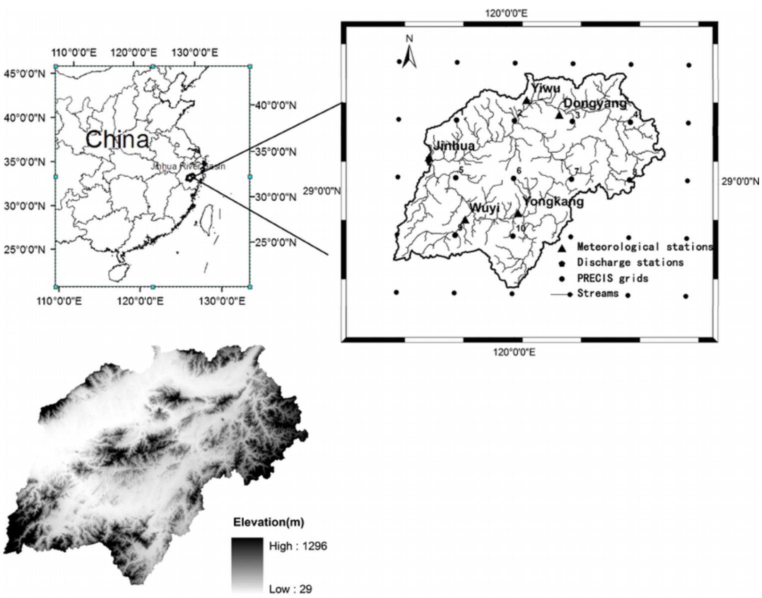


Figure 1: Study area (Xu et al., 2014)

2.2 DHSVM

In this study version 3.1.1 of the distributed hydrology-soil-vegetation model (DHSVM) will be used. This model is a physically-based, distributed model, created by Wigmosta, Vail, and Lettenmaier (1994) and consists of seven modules: evapotranspiration, snow pack accumulation and snow melt, canopy snow interception and release, unsaturated moisture movement, subsurface flow, surface overland flow and channel flow. A short elaboration of each of these modules is given in Appendix A.

This model uses digital elevation model (DEM) data to identify the spatial scale at which a representation of hydrology-vegetation dynamics is provided. The resolution of this model is typically between 10 and 200 meters. The study area is divided into computational grid cells that are based upon the chosen DEM resolution. Each of these grid cells is centred on each DEM point and is allocated soil and vegetation characteristics. DHSVM offers simultaneous solutions to water and energy balance equations for every grid cell in the river basin. The hydrological connection of individual grid cells is realised by surface and subsurface flow routing, schematised in Figure 2. DHSVM adopts a cell-by-cell method to route saturated subsurface flow using a kinematic or diffusion approximation (Wigmosta, Vail, and Lettenmaier, 1994; Wigmosta, Nijssen, and Storck, 2002). For the surface flow routing can be chosen between a unit hydrograph method and an explicit cell-by-cell method. In this study the explicit cell-by-cell method is implemented, since the model provided that has been used by Pan et al., 2017 was set to this method. This explicit cell-by-cell method uses stream network files that are based on the DEM to determine the flow direction of the water.

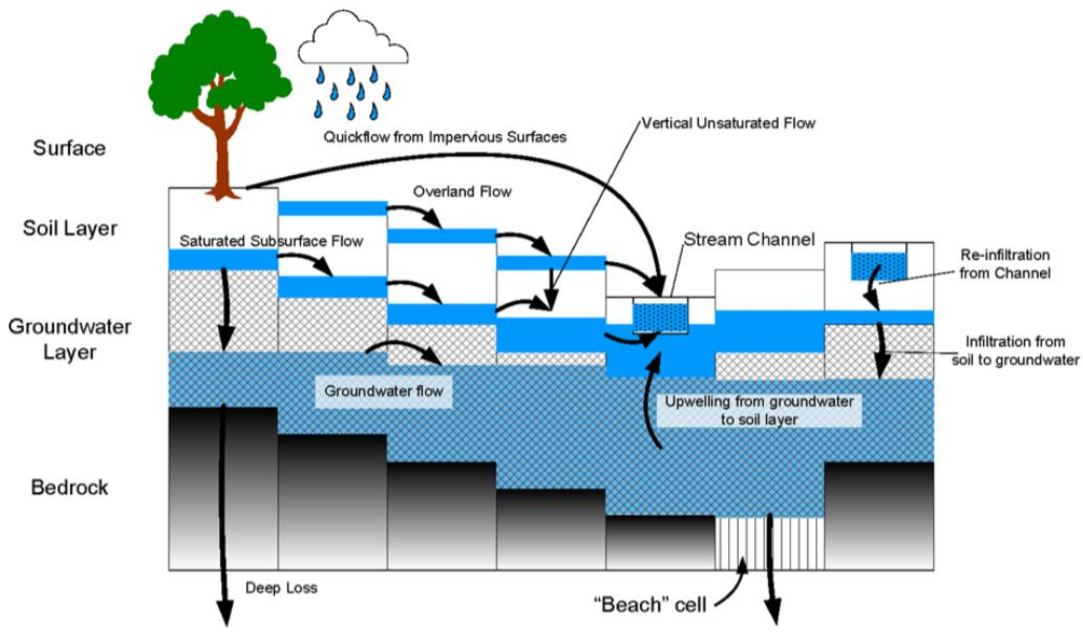


Figure 2: Schematisation of DHSVM (Washington University, 2006)

The parameters within DHSVM can be subdivided into elevation, stream, road, soil and vegetation categories. The parameters that are related to the characteristics of the stream network are determined based on the DEM data. These parameters therefore do not have to be calibrated. The soil and vegetation parameters that have a physical meaning on the other hand do need to be calibrated when their value is not known through observations, which is generally the case. Since there are more than 20 parameters with a physical meaning present in the model (Wigmosta, Nijssen, et al., 2002; Cuo et al., 2011) and the computational time is long, calibration is not an easy task (Xu et al., 2014). The model parameters that are used for calibration in the Jinhua river basin are summarised in Table 2. Xu et al. (2014) used a trial-and-error approach to calibrate the model for the Jinhua river basin. In the mean time an optimisation algorithm has been written based on ε-NSGA-II multi-objective algorithm, which is further elaborated on in Section 2.3.

Table 2: Model parameters used for calibration ((Xu et al., 2014)

Parameter	Abbrev.	Description	Unit
Soil parameters			
Lateral saturated hydraulic conductivity	K_{ls}	Used in calculation of lateral flow movement	m/s
Exponential decrease rate of K_{ls} with soil depth	EDR	Exponent describing the decrease of K_{ls} with soil depth	-
Maximum infiltration capacity	MIC	Maximum rate of soil infiltration	m/s
Field capacity	f_c	Used to estimated available water for subsurface layers	m^3/m^3
Wilting point	w_p	Used in the evaporation calculation	m^3/m^3
Vegetation parameters			
Maximum stomatal resistance	R_{smax}	Used in calculation of canopy resistance	s/m
Minimum stomatal resistance	R_{smin}	Used in calculation of canopy resistance	s/m
Overstory leaf area index	OLAI	Used in calculation of canopy resistance, snow interception, radiation balance	-
Aerodynamic extinction factor	AEF	Used in calculation of aerodynamic resistance	-

2.3 ε-NSGA-II

To be able to calibrate the model for a situation with a higher representation of precipitation data an algorithm is necessary. The algorithm that was available for this model is based on the Epsilon-Dominance Non-Dominated Sorted Genetic Algorithm II (ε-NSGA-II). Kollat and Reed (2006) did a study to compare the performances of four evolutionary multi-objective optimisation (EMO) algorithms: the Non-Dominated Sorted Genetic Algorithm II (NSGAII), the Epsilon-Dominance Non-Dominated Sorted Genetic Algorithm II (ε-NSGAII), the Epsilon-Dominance Multi-Objective Evolutionary Algorithm (εMOEA), and the Strength Pareto Evolutionary Algorithm 2 (SPEA2). The algorithms were compared using runtime performance metrics (convergence, diversity and ε-indicator), unary metrics (hypervolume indicator and ε-indicator) and the first-order empirical attainment function. Kollat and Reed (2006) concluded that the performance of the ε-NSGAII greatly exceeds the performance of the NSGAII and the εMOEA. The ε-NSGAII also achieves superior performance relative to the SPEA2 in terms of search effectiveness and efficiency.

The Non-Dominated Sorted Genetic Algorithm II (NSGA-II) is a generational evolutionary multi-objective optimization (EMO) that aims at approximating the Pareto-optimal fronts for a given problem while keeping high diversity in its solutions set (Deb et al., 2002). The Pareto-optimal fronts define Pareto-optimal solutions where none of the objective functions values can be improved without degrading some of the other objective function value. Deb et al. (2002) describes three modules that are used within this algorithm:

1. Non-dominated sorting
2. Crowding distance assignment
3. Crowded comparison operator

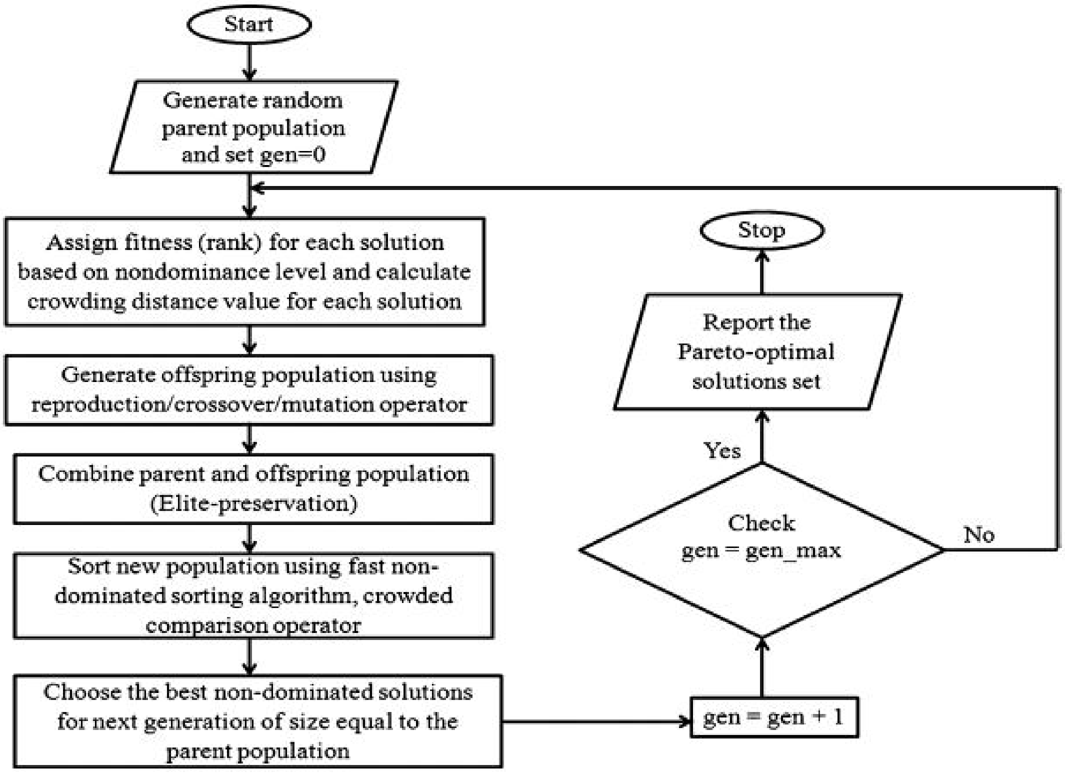


Figure 3: Flow chart of NSGA-II (Kumar and Yadav, 2017)

According to Kumar and Yadav (2017) the procedure followed by NSGA-II can be explained in four steps. These steps are described below and can be summarised in a flow chart, which is visualised in Figure 3.

Step 1 Combine parent (P_t) and offspring (Q_t) populations to create $R_t = P_t \cup Q_t$. Perform a non-dominated sorting to R_t and identify different fronts: $F_i, i = 1, 2, ...,$ etc.

Step 2 Set new population $P_{t+1} = \emptyset$. Set a counter $i = 1$. Until $|P_{t+1}| + |F_i| < N$ (N is population size), perform $P_{t+1} = P_{t+1} \cup F_i$ and $i = i + 1$.

Step 3 Perform the crowding sort procedure (i.e., assign crowding distance and apply crowded comparison operator) and include the widely spread $N - |P_{t+1}|$ solutions by using the crowding distance values in the sorted F_i to P_{t+1}.

Step 4 Create offspring population Q_{t+1} from P_{t+1} by using the crowded tournament selection, crossover and mutation operators.

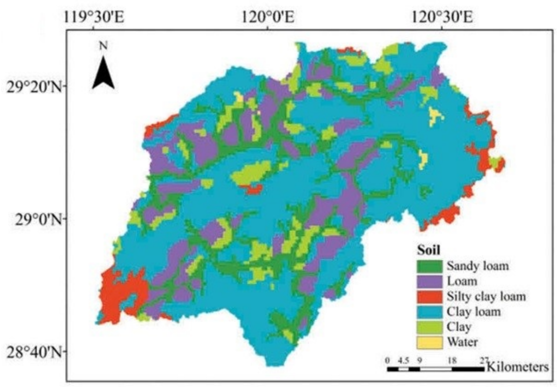
The Epsilon-Dominance Non-Dominated Sorted Genetic Algorithm II (ε-NSGA-II) is a modified version of NSGA-II (Deb et al., 2002; Reed and Devireddy, 2004; Ren and Li, 2007). Through epsilon-dominance archiving, dynamic population sizing and automatic termination this algorithm eliminated much of the traditional trial-and-error parameter estimation associated with EMO algorithms. (Kollat and Reed, 2006). Compared to other EMO algorithms ε-NSGA-II exceeds their performance greatly. Also due to the its simplified parameter estimation, its ability to adaptively size its population and the automatic termination, this algorithm is efficient and reliable (Kollat and Reed, 2006).

2.4 Data

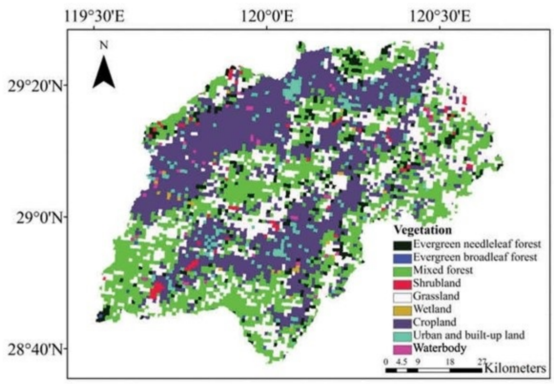
2.4.1 Initial data

The data needed for this model include climate data (average air temperature, wind speed, relative humidity, sunshine hours and precipitation), watershed boundary (mask), DEM data, vegetation and soil type, soil depth and stream network. In previous studies this data is obtained for the Jinhua river basin through various sources. Daily climate data are obtained from five meteorological stations (Dongyang, Jinhua, Wuyi, Yiwu and Yongkang) throughout the area that are indicated in Figure 1. This data is available from 1962 until 2011 for the Wuyi station and from 1962 until 2014 for the other four stations, see Table 3. The observed run off used for calculating the model performance is obtained from the Jinhua discharge station and is for this research available from November 2003 until December 2008. The data used in the first part of this study runs from November 2003 until December 2008, where the first two months of this data are used for the spin up time of the model.

DEM data is downloaded from the Shuttle Radar Topography Mission (SRTM) at a resolution of 90 meters. This data is redefined to a resolution of 200 meters by Xu et al. (2014). The soil and vegetation data are obtained from the US Department of Agriculture (USDA) and WESTDC Land Cover Products 2.0, respectively (Pan et al., 2017; Xu et al., 2014). A map of the soil and vegetation data is shown in Figure 4. Arc Workstation software was used to generate the soil depths and stream network using the DEM and mask file. The prepared soil depths, stream files, DEM and mask data were provided by Suli Pan for this research.



(a) Soil type in the Jinhua river basin



(b) Vegetation in the Jinhua river basin

Figure 4: Distribution of soil and vegetation types in the Jinhua river basin (Pan et al., 2017)

2.4.2 Data for model improvement

For the second part, where the model performance is tried to be improved, additional meteorological data is used. The data is obtained from the same hydrological bureau as the first five stations came from. However, it contains hourly data, which was aggregated to daily data, because that is what the model requires. The data provided is from 23 meteorological stations throughout the Jinhua river basin, Figure 5. Included in these 23 stations are four of the five stations that were used initially. The fifth station was added, so 24 stations were available for the second part of the study. Additional information on these stations can be found in Table 3.

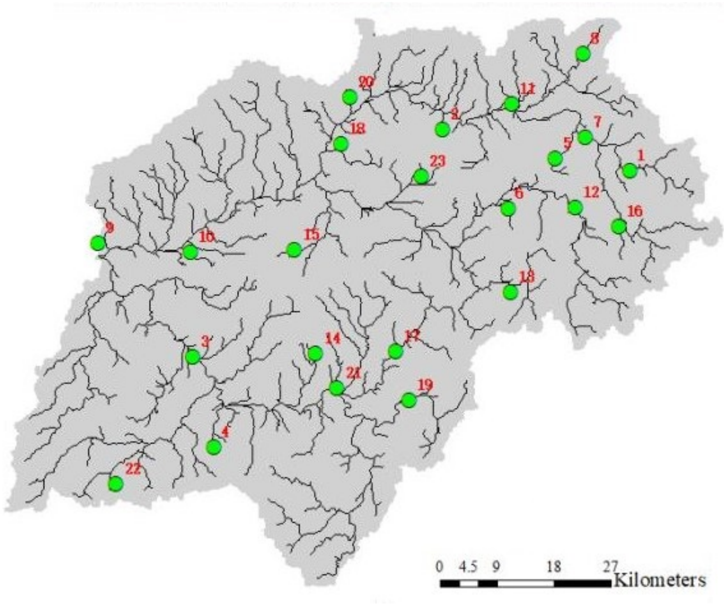


Figure 5: Locations of additional stations. Numbers correspond with Table 3

DHSVM needs at each location of a meteorological station the air temperature, precipitation, relative humidity, wind speed, incoming shortwave and longwave radiation. These last two are calculated from the sunshine hours that are measured at the meteorological stations. The time period in which the data is available differs per station and due to that the sunshine hours are not measured at all stations. The period at which data from all stations is available is from July 2007 until December 2011. The short and long wave radiation at the stations where the sunshine hours are missing are found through interpolation using the nearest neighbour technique and the stations where this data was available.

The observed discharges, however, are only available until December 2008, which makes the usable period of the stations even shorter. It has therefore been decided that the stations of which the time period does not start before August 11th 2006 will be removed, which leaves 21 stations for further improvement of the model. This date was chosen because previous research has showed that it is possible to calibrate a model with one year of data (Brown et al., 2013; Sun et al., 2016) and using this date leaves a large amount of stations that can be used.

Table 3: Overview of additional and original stations in the Jinhua river basin. Italic text indicates station in initial dataset

	Station	Latitude [°]	Longitude [°]	Elevation [m]	Time period	Total precipitation 2008 [mm]
1	Bada	29.2	120.5	164	2006.01.01-2014.08.31	901
2	*Dongyang*	*29.3*	*120.2*	*92*	*1962.01.01-2014.08.31*	*1264*
3	Futang	29.0	119.8	73	2006.01.01-2014.08.31	1273
4	Guodong	28.8	119.8	197	2006.01.01-2014.08.31	1268
5	Guozhai	29.2	120.4	466	2006.01.01-2013.05.06	787
6	Hengdian	29.2	120.3	110	2006.01.01-2014.08.31	901
7	Hengjin	29.3	120.5	136	2006.01.01-2014.08.31	1130
8	Hulu	29.4	120.5	139	2006.08.11-2014.08.31	826
9	*Jinhua*	*29.1*	*119.7*	*63*	*1962.01.01-2014.08.31*	*1374*
10	Lipu	29.1	119.8	110	2006.08.11-2014.08.31	1037
11	Liushi	29.3	120.3	88	2006.01.01-2014.08.31	745
12	Nanjiang	29.2	120.4	180	2006.08.11-2014.08.31	1367
13	Qianxiang	29.0	120.3	158	2006.09.04-2014.08.31	874
14	Shanghuang	29.0	120.0	130	2006.08.11-2014.08.31	1273
15	Shanyang	29.1	120.0	145	2006.01.01-2014.08.31	974
16	Shuangxi	29.1	120.5	251	2006.12.27-2014.08.31	1367
17	Xian	29.0	120.1	130	2006.08.11-2014.08.31	1107
18	Xuchu	29.3	120.1	73	2006.08.11-2014.08.31	1158
19	Yangxi	28.9	120.2	179	2006.01.01-2014.08.31	874
20	*Yiwu*	*29.3*	*120.1*	*75*	*1962.01.01-2014.08.31*	*1283*
21	*Yongkang*	*28.9*	*120.0*	*90*	*1962.01.01-2014.08.31*	*1234*
22	Yuyuan	28.8	119.7	207	2006.08.11-2014.08.31	1204
23	Zhenjia	29.2	120.2	329	2007.06.23-2014.08.31	1139
24	*Wuyi*	*28.8*	*119.8*	*90*	*1962.01.01-2011.12.31*	*1251*

3 Methodology

This chapter gives a description of the method used to answer the research questions phrased above. Section 3.1 will go into detail about the method of answering the first research question regarding the influence of precipitation data on the model results. After this the method of finding the influence of the parameter estimation on the simulated discharge will be given in Section 3.2. And finally, the method used to improve the model is discussed in Section 3.3.

3.1 Influence of precipitation data on (peak) discharge simulation

The first research question consists of two parts. The first part examines the current treatment of the precipitation data and second part deals with the influence of the precipitation data on the (peak) discharge simulation. In this section the methods to answer both of these parts are described in this order. The results of this research question will show whether the influence of precipitation on the (peak) discharge simulation is large enough to consider in the final step of the research, where an attempt was made to improve the model performance, and possible measures to improve the precipitation data.

3.1.1 Current precipitation data

Precipitation data is an important input parameter for the generation of run off, as described above. It is important that the data used in the model is treated and corrected well. If this is not the case, this might be a source of incorrect run off generation within the model. In the first step of this research there is therefore looked into the precipitation data. The correction for structural errors, such as wind, evaporation and wetting loss, of the measured precipitation is important, since this can introduce significant errors, resulting in an underestimation of the precipitation (Wagner, 2009). Also during interpolation it is important to take into account that due to an increased elevation the precipitation might increase as well (Subarna et al., 2014). So, if this is not corrected for it is a possible cause of underestimating the peak flow. To ensure that the peak flows are not underestimated due to incorrect data treatment, the corrections done on the data need to be identified. This is done on the basis of information obtained from the researchers that previously used the data and model for the same river basin, and confirming this with the precipitation output. Also to see the extent of the underestimation the amount of simulated discharge will be calculated using the unchanged values of the precipitation and parameters (from now on indicated as the initial state) and subsequently compared to that of the observed discharges.

3.1.2 Model sensitivity to precipitation

Secondly the sensitivity of the model to precipitation is analysed. This is done by synthetically increasing and decreasing the precipitation input of the model. The precipitation is set to be 10% and 20% less and more than the initial state for all the meteorological stations. In this analysis the mass balance will also be taken into account. The sensitivity of the model is evaluated using the mean values of the discharge, to see in what way this increases. After determining the influence of precipitation data on the model output the data will be set to its original (the initial state) values for further analysis.

The influence of the precipitation on peak discharges is found through a correlation analysis. For this analysis the peak discharges are determined first using the Peaks Over Threshold (POT) method that has been used in previous studies for this area. The POT method selects all peaks over a certain threshold, which can therefore result in more than one peak per year (Lang et al., 1999). Liu et al. (2017) determined that the peak threshold for independent peaks in the Jinhua river basin is 340 m^3/s. Each of these peaks is tested for independence according to criteria set by USWRC (1976). These criteria state that the interval between two consecutive peak flows has to be larger than five days plus the natural logarithm of the basin in square miles, and the intermediate flows between these two consecutive peaks must drop below 75% of the lowest of these two flood events. After this the highest correlation between the peak discharges and precipitation is determined. This is done through selecting an appropriate time lag and temporal scale for the precipitation. Different combinations are made of time lags varying from 0 to 19 days and temporal scale varying from 1 to 19 days. These ranges are chosen, because larger time lags and temporal scales are not realistic for areas similar to the Jinhua river basin (M. Booij, personal communication, March 27, 2018). A moving average with a window the size of the desired temporal scale is used to obtain the different temporal scales. The different time lags are obtained by selecting the precipitation event the desired amount of days before the peak flow occurs. For each of the combinations the correlation coefficient with the peak discharges will be calculated resulting in the highest correlation for the most appropriate combination of time lag and temporal scale.

3.2 Influence of the parameter estimation on (peak) discharge simulation

Besides the precipitation data that can cause the underestimation of the peak flows, the parameter estimation will also introduce an error in discharge simulation. To get a better understanding of the error from the parameter set, the consequences of this error on (peak) discharge simulation are analysed. Pan et al. (2017) did a two-step sensitivity analysis to find the parameters in the model that the simulated discharge in the Jinhua river basin is sensitive to. The seven parameters that were found in this study will be used to see in what way the model responses when they are changed, also with regard to peak flows. For the sensitivity analysis a univariate method is used. The value of the parameters will be changed by setting them individually to the maximum and minimum value of the range that was provided in Pan et al. (2017) and three equally distanced values in between this range. When the run of one parameter is finished it will be set back to its initial value. The simulated discharges that result from this will be visualised. These visualisations will be analysed, also using again the mean discharge it can be seen in what extent the parameter estimation affects the discharge simulation.

The effect of parameter changes has been investigated both for the mean discharge result, and for the resulting discharge series. For this the Nash-Sutcliffe coefficient (see Equation (1)) and PBIAS (see Equation (2)) are used, since Pan et al. (2017) and Xu et al. (2014) used these in previous studies as well. After this the effect on the peak discharges is analysed also by looking at the model performance. The independent peaks are localised in the same manner as has been done in the previous research question. For the analysis of the model performance only the peaks are used that occur in the observations as well as in the simulation. For this a window of three days has been used, in case a simulated peak occurs a day earlier or later than the observed peak. When the moments of the occurring peaks are selected, these are used to calculate the NS- and PBIAS-value.

$$NS = 1.0 - \frac{\sum_{i=1}^{N}(O_i - S_i)^2}{\sum_{i=1}^{N}(O_i - \bar{O})^2} \quad (1)$$

$$PBIAS(\%) = 100\% \times \frac{\sum_{i=1}^{N}(S_i - O_i)}{\sum_{i=1}^{N}(O_i)} \quad (2)$$

In these equations S_i is the simulated discharge at time step i and O_i is the observed discharge at time step i.

3.3 Improving current model results

To improve the model performance several steps can be undertaken. Each of these steps will be discussed in this paragraph. First, the systematic measurement errors that are still present in the currently used data shall be removed. The method used to remove the measurement errors is described in Section 3.3.1. After this more meteorological stations shall be added to the model with what the rainfall representation of the, amongst other things, precipitation data will be higher. The method regarding this is described in Section 3.3.2. Finally, an attempt has been made to improve the model through parameter optimisation. This can be found in Section 3.3.3.

3.3.1 Removing measurement errors

While measuring precipitation a number of errors can occur. Several studies have been done to correcting those errors and all conclude that wind induced errors are the most severe errors (Balin et al., 2010; Ren and Li, 2007; Wagner, 2009). Balin et al. (2010) examined if uncertain point precipitation data is likely to affect the output of distributed hydrological models. They conclude that precipitation input uncertainty in a distributed model did not lead to substantially different results in terms of simulated discharge and model efficiency, contrary to previous studies. A comparison of the effects on simulated discharge was made between three variants of input data, namely, using data that was corrected for systematic errors, data that was corrected for random errors, and uncorrected data. It turned out that the data with correction for systematic errors had a larger effect on discharge simulation than when data with correction for random errors was used. Ren and Li (2007) named different errors that occur during precipitation measurements and introduced a correction method for this using a pit gauge, two operational gauges and a horizontal gauge in China. They focus mainly on the wind induced errors, since this is the main source of errors in precipitation measurements. Ren and Li (2007) state that rain gauges in China are designed to prevent evaporation loss and losses due to splashing in and out of precipitation. Therefore the data does not need to be corrected for this. Wetting losses, however, can occur in China. According to Ren and Li (2007) wetting losses are around 0.2 mm in China when the inner walls are sufficiently wetted. Other systematic errors are also not corrected for, since these were said not to be of significant influence (Ren and Li, 2007).

At the meteorological stations in this study the precipitation was measured using a 8 inch (324 cm^2) standard rain gauge (SRG) placed two meters above the ground (S. Pan, personal communication, April 11, 2018). These type of rain gauges are non-recording gauges and are a standard in the US (Legates and DeLiberty, 1993). Legates and DeLiberty (1993) named a correction factor k_r to correct the precipitation for the wind induced error, see Equation (3). In this equation U_w is the wind speed at the height of the gauge orifice in m/s. It is assumed that the wind speed is measured at the same height as where the gage orifice is located. The measured liquid precipitation is multiplied by this correction factor.

$$k_r = \frac{100}{100 - 2.12 \cdot U_w} \tag{3}$$

Combining the important corrections as found in the literature the equation for the corrected precipitation looks like Equation (4). In this equation P_c is the corrected precipitation, P_0 is the measured precipitation, both in mm, k_r is the correction factor given in Equation (3) and WL is the wetting loss as is given in Ren and Li (2007) also in mm.

$$P_c = k_r \cdot P_0 + WL \tag{4}$$

After the correction of the measured precipitation an analysis was done of how the model performance has changed with regard to the entire discharge simulation as well as the peak discharge simulation, using the Nash-Sutcliffe coefficient and the PBIAS. The model performance of the peaks will be done in the same manner as has been explained in Section 3.1, even though no additional calibration has taken place yet.

3.3.2 Introducing more meteorological stations

To increase the rainfall representation of the used precipitation data 16 other meteorological stations were introduced into the model. Although the data comes from the same hydrological bureau it is not presented in the same manner and not even all necessary variables were measured. It is therefore necessary to prepare the data in such a way that it is usable in the model that is currently used.

Preparation of the precipitation, mean air temperature, relative humidity and wind speed data that were measured here included aggregating the hourly data to daily data. The variable that was missing from these stations is the sunshine hours, needed to calculate the short and long wave radiation. These two missing variables are obtained for the stations by interpolating the values provided by the five stations that were used in the first part of the research. The precipitation data that was measured at these stations is prepared in the same manner used for the first five stations, described in Section 4.1.1. Before the data is used in the model it is treated for structural measurement errors in the same way as has been done for the initial five stations, see Section 3.3.1.

After the model has been run, the results will be visualised again in the same ways that has been done previously and it will be analysed. For this analysis the Nash-Sutcliffe coefficient and the PBIAS-value will be used again.

3.3.3 Model parameter optimisation

After the implementation of additional data points and the correction for the systematic measurement errors in precipitation data the model will have to be recalibrated. The calibration has been done by using an automatic multi-objective calibration algorithm that was already available for DHSVM and this catchment area. The algorithm is based on the Epsilon-Dominance Non-Dominated Sorted Genetic Algorithm II (ε-NSGA-II), a modified version of NSGA-II (Deb et al., 2002; Reed and Devireddy, 2004; Ren and Li, 2007). The algorithm will run on the server available at the Zhejiang University that is able to use parallel computation. The algorithm is set to have a maximum of 50 generations in each run and for each generation the population size has a minimum of 12 and a maximum of 96. The algorithm will be terminated once the epsilon dominance is smaller than a certain value, which is set to 0.025 for all objectives, or when 3000 function evaluations have taken place.

There are three objectives used in the calibration. The Nash-Sutcliffe coefficient and PBIAS are chosen since previous calibration has also been done with these objectives. To have a larger focus on the peak flows during the calibration the Mean Fourth-power Error (see Equation (5)) has been chosen as the third objective (T. Rientjes, personal communication, April 19, 2018). During the calibration all objectives will be taken into account simultaneously to find the optimum parameter set. For calibration five parameters have been selected that were found to affect the peak flows the most, according to the small sensitivity analysis that has been performed during the second research question. These parameters are the rain LAI multiplier (Rj), porosity (ϕ), lateral conductivity (K), field capacity (θ_{fc}) and the wilting point (θ_{wp}) of the clay loam soil.

$$M4E = \frac{1}{N}\sum_{i=1}^{N}(O_i - S_i)^4 \tag{5}$$

As stated in Section 2.4.2 the common period of the data from all the meteorological stations combined with the available observed discharges is limited. The choice to not synthetically increase the data series for the different stations through interpolation was made, because this does not truly increase the rainfall representation and because otherwise possible additional errors are introduced. This leaves approximately 2.5 years for calibration and validation. The calibration period will be from August 2006 until December 2007 and the validation period will be from January 2008 until December 2008. This is a short period for calibration and validation which can affect the overall findings of this study. However, this may lead to good results as has been seen in previous studies where also limited data was available (Brown et al., 2013; Sun et al., 2016). The number of peaks that are available for analysis in these periods is limited. The NS and PBIAS value will be calculated, however the comparison between the initial state and the improved model versions will mainly be done visually. This is because the calculation of these objectives with the limited data points is probably not robust enough to draw conclusions from.

Since the optimisation is performed with an extra objective that introduces an extra focus on the peak discharges, the choice was made to also apply this optimisation to the model with 5 stations where the precipitation was corrected for structural measurement errors as well. This was done so the comparison between the two situations would be more fair.

During the preparation of the files for the calibration of the model it became clear that the ε-NSGA-II algorithm as it is now, is a difficult to understand piece of coding. Also, it is not well documented what should be changed in what manner to make the algorithm usable for another situation. Due to this, the preparation progress took a few weeks, before everything was working as it should. To safe the trouble of figuring out what to change in the algorithm for new scenarios in the future, a small documentation of the steps needed in this research has been written and included in Appendix B.

4 Results

In this chapter the results of the research questions are given. Section 4.1 describes the results of the first research question regarding the current precipitation data that have been used in the model. After this the influence of the model parameters is discussed in Section 4.2. Finally, the model improvement will be described in Section 4.3.

4.1 Influence of precipitation data on (peak) discharge simulation

The first research question consists of two parts. First the current treatment of the precipitation data and second the influence of the precipitation data on the (peak) discharge simulation. In this section the results of both these parts are described in this order. This research question will show whether the influence of precipitation on the (peak) discharge simulation is large enough to consider in the final step of the research, where the model performance is tried to be improved, and what can possibly be done to improve the precipitation data.

4.1.1 Current precipitation data

The currently used precipitation data comes from five meteorological stations that are located throughout the study area. The data that is used starts at 01/11/2003 and ends at 31/12/2008. The first two months of the data are used for the spin up period for the model, so from 01/01/2004 the output of the model can be used for evaluation. According to S. Pan (personal communication, March 15, 2018) the data has not been corrected for systematic measurement errors before it was used as model input. These systematic measurement errors include, among other, wind induced errors and, wetting and evaporation loss (Wagner, 2009). The measurement errors that occurred due to failing equipment have been removed and corrected for. Since the model underestimates the peak flows, the extent of the water shortage in the model is analysed through calculating the total amount of water that has left the area as discharge according to observations and simulation. Over 4 years the model simulated the total discharge as 1.66E+10 m^3. According to the observations the total discharge over 4 years is 1.69E+10 m^3. The difference between these two is 2.07E+08 m^3, which corresponds to a shortage of approximately 1.2% in the model.

According to Wigmosta, Vail, and Lettenmaier (1994) the model uses digital elevation data to model the topographic controls on precipitation. S. Pan (personal communication, March 15, 2018) stated that this includes the height correction needed for the precipitation. When looking into the code the equation for the precipitation lapse rate can be found. The lapse rate equation is a linear equation, see Equation (6), as was noted by Gwozdz (2009). However, Liston and Elder (2006) proposed a non-linear equation, as is given in Equation (7). A a linear formula as is used in the model cannot be found in literature.

$$P = P_0 \left[1.0 + \chi(z - z_0)\right] \tag{6}$$

$$P = P_0 \left[\frac{1.0 + \chi(z - z_0)}{1.0 - \chi(z - z_0)}\right] \tag{7}$$

There is no universal equation for the precipitation lapse rate, since this greatly depends on geographic factors. Moreover, determining the precipitation lapse rate is a difficult task, which for a specific area is ideally based on annually measured precipitation sums at different elevations. If there are no observations available to determine the lapse rate, the most standard and relatively simple equation should be used (M. Booij, personal communication, April 5, 2018). When making a scatter plot using the precipitation data from the five stations in the year 2004 and their elevation, the best fitted equation is a linear equation. Therefore the equation will not be changed and remain linear in the model.

4.1.2 Correlation of precipitation and (peak) discharge

Next, the influence of the precipitation on the discharge generation by the model is investigated. By manually increasing and decreasing the data the effect on the discharges in the river can be determined, see Figure 6. When looking at the average value of the discharge it can be seen that the discharge does not respond linearly with the precipitation. When the precipitation is changed with 10% the discharge changes with approximately 20%, while the mass balance error according to the model remains low, see Table 4. An explanation for this can be that because of the change in precipitation a lower percentage goes into storage due to the filling of storage by preceding precipitation events. Consequently a higher percentage of the precipitation goes into run off. The final storage for the different scenarios can be seen in Table 4, where it is visible that with a higher precipitation intensity the storage is less emptied than with a lower precipitation intensity. Also the change in storage over time is visualised in Figure 7. In Figure 8 the percentage saturated cells in the river basin is plotted and the precipitation that has fallen over the entire area at each time step. From this figure it is visible that the increase in precipitation also results in a increase in the saturation extent of the river basin. On the other hand it is also visible that after the heaviest rainfall event of the four years the saturation percentage only goes up to about 45%. Besides that the time when this event takes place is odd, the response of the catchment is also different than one would expect. The reason why the percentage of saturated cells does not increase more is not known.

From the mass balance the total amount of precipitation in the river basin for the different scenarios at each time step was extracted. In Figure 9 the precipitation and discharge are plotted in one figure. From this it is clearly visible that peaks in precipitation and discharge occur around the same time, which is expected. Less clearly visible is, that the peaks do not occur at the exact same time, but that there is a small delay between the two peaks. This indicates that the correlation between these physical quantities is largest with a time lag. To verify this a correlation analysis has been performed.

Since the study mainly focusses on the effect of precipitation on peak discharges, the above mentioned correlation analysis is done for the precipitation and peak discharges. Correlations with the peak discharges were calculated using different combinations of time lags and temporal

Table 4: Sensitivity of model on precipitation in numbers

Precipitation input	-20%	-10%	Initial	+10%	+20%
Mean discharge (m^3/s)	68.5	85.8	104.4	124.0	144.4
Percentage from initial state	66%	82%	100%	119%	138%
Initial storage (mm)	259.6	259.6	259.6	259.6	259.6
Final storage (mm)	205.7	210.7	214.7	217.5	219.9
Absolute mass balance error (mm)	-0.224	-0.222	-0.228	-0.223	-0.241
Relative error (%)	0.42	0.45	0.51	0.53	0.61

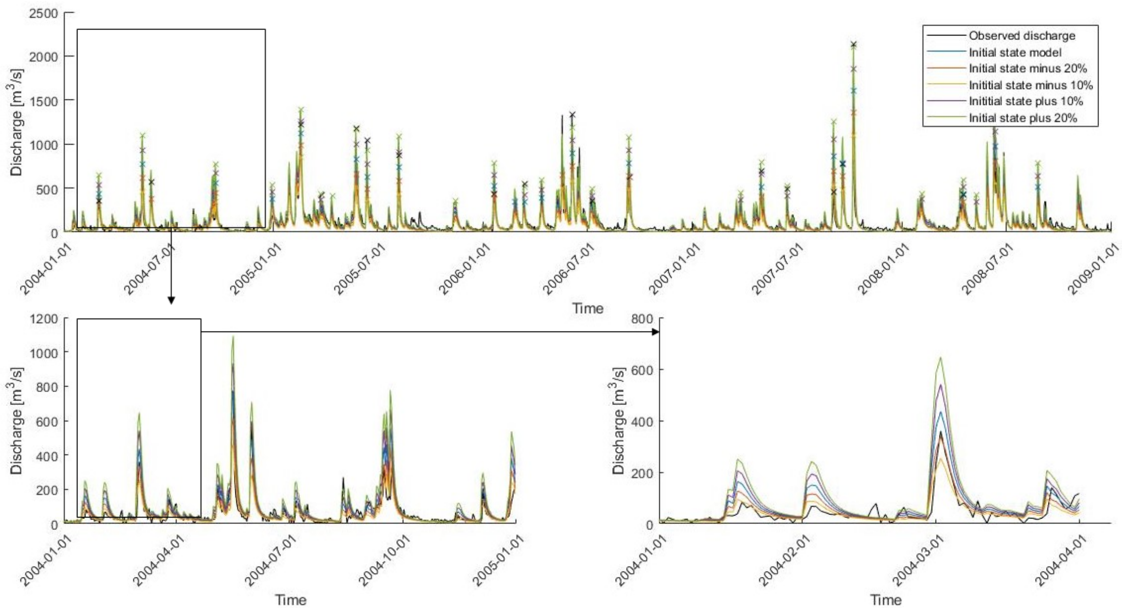


Figure 6: Model sensitivity to precipitation. Crosses indicate the peak flows

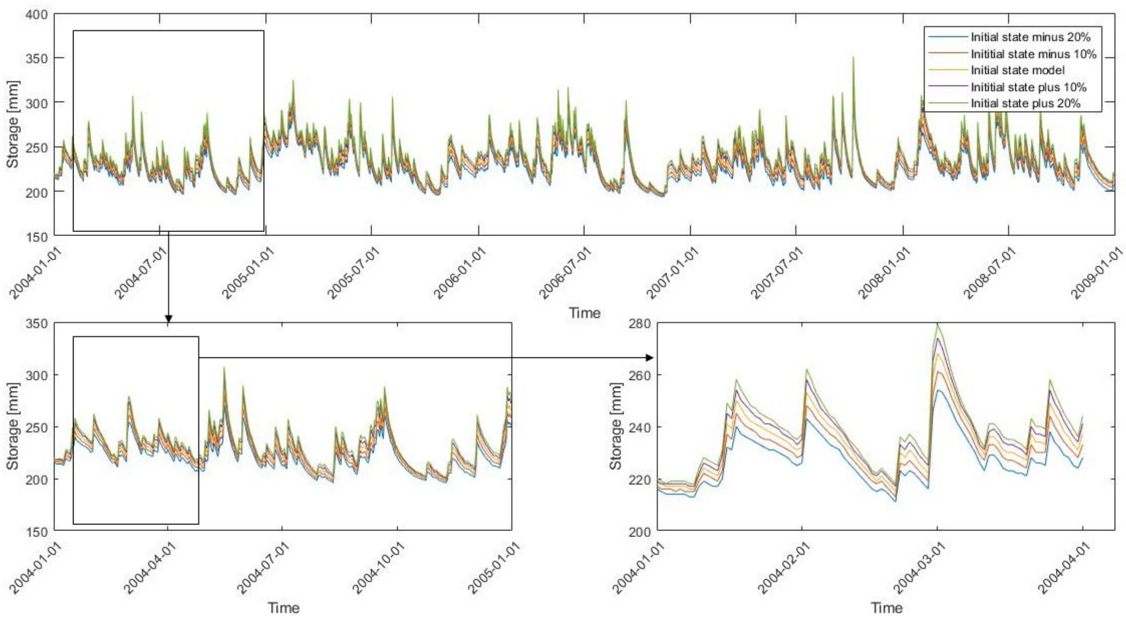


Figure 7: Water storage in the area

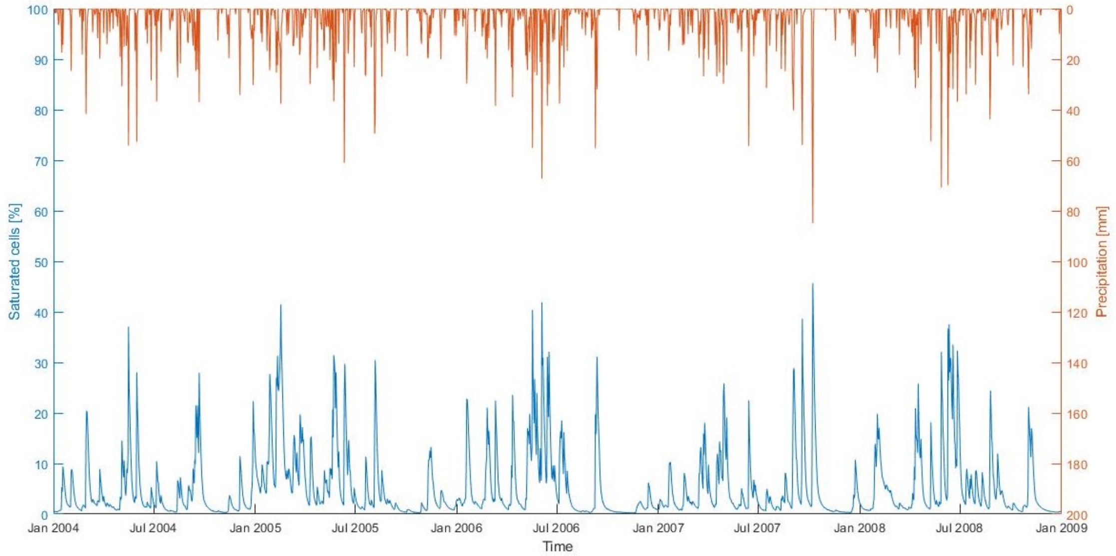


Figure 8: Percentage saturated cells and precipitation at each time step

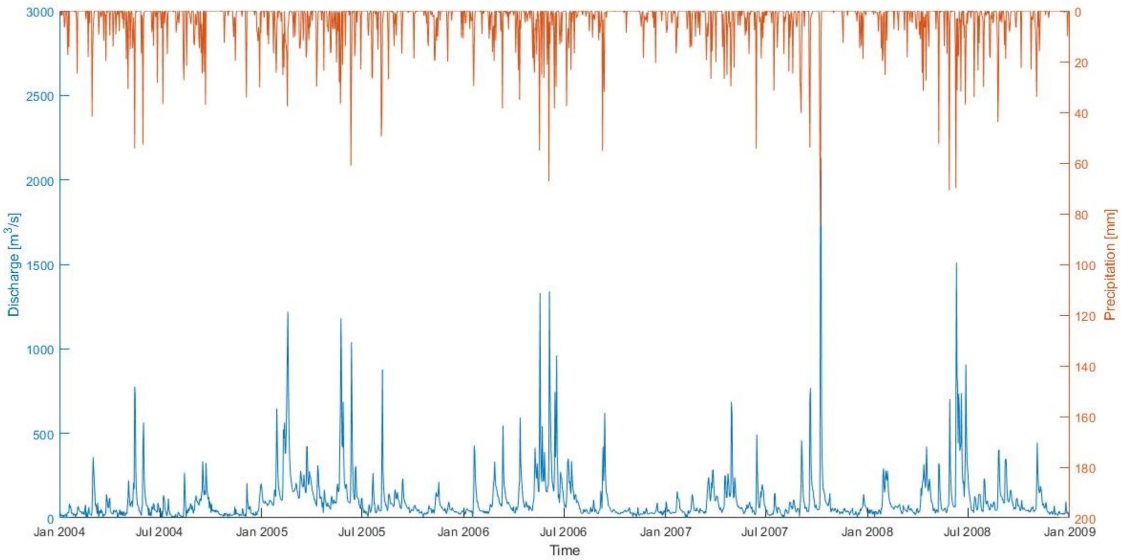


Figure 9: Discharge and precipitation at each time step

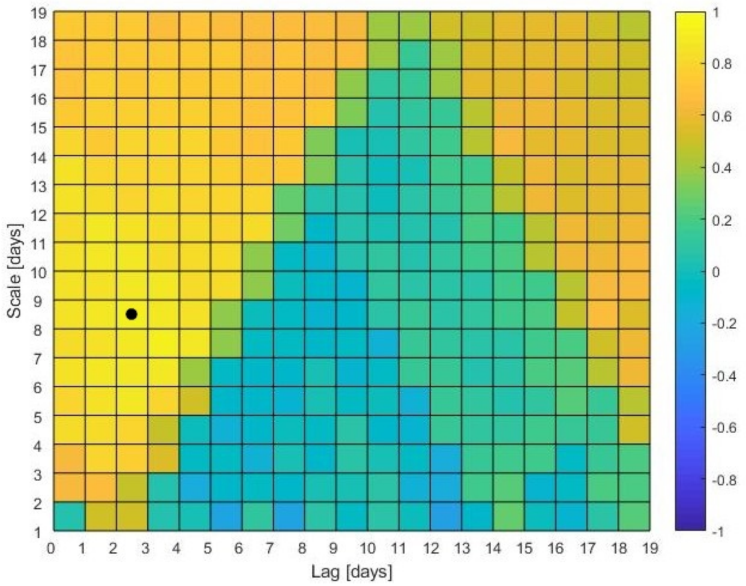


Figure 10: Correlation between peak discharge and precipitation for different time lags and temporal scales. Highest correlation is 0.93 and indicated with a black dot

resolution of the precipitation that were generated as was explained in Section 3.1. The correlations that were calculated are visualised in a colour map, see Figure 10. The highest correlation coefficient was found at a time lag of 2 days and a temporal scale of 8 days and had a value of 0.93. Which is with a 95% confidence interval a significant correlation.

4.1.3 Conclusion

The addressed research question in this section is: How is the currently used precipitation data treated and what is the effect of precipitation data on peak flow simulation? The answer to this can be divided into two parts. First, it has become clear that the data that is currently used has been cleared of measurement errors due to failure of equipment. Also, the model already corrects for height when interpolating the precipitation. However, structural errors in the measurements such as wind induced errors and, wetting and evaporation loss are not corrected for. This correction might help to improve the simulation of peak discharges. The second part of this research question further examined the relation between precipitation and (peak) discharges. It was found that precipitation correlates with discharge in a non linear relationship. When the precipitation was changed with 10%, the discharge changed with almost 20%. It was also visible that the precipitation and discharge peaks occurred around the same time, which indicated that there is a relation between the two physical quantities. The relation between the precipitation and peak discharges was examined through a correlation assessment that varied the time lag and temporal scale of the precipitation to find what combination of these two caused the highest correlation. It turned out that for a temporal scale of 8 days and a time lag of 2 days, the correlation between peak discharge and precipitation was at its highest (R=0.93). From this it can be concluded that the precipitation has a significant influence on (peak) discharge simulation and it is worthwhile to use the precipitation as a way to improve the model performance.

4.2 Influence of the model on (peak) discharge simulation

Besides the precipitation it is also a possibility that the model parameters are an important cause for the underestimation of peak discharges. Therefore this will be looked into this in the following paragraph.

4.2.1 Effect of parameter estimation on discharge generation

In this paragraph it is examined how the parameter estimation influences the simulation of the discharge. First, the sensitive parameters were selected from Pan et al. (2017), who found through a two-step sensitivity analysis that DHSVM applied in this river basin is most sensitive to the following parameters:

1. Root zone depth of crop land (D)
2. Lateral conductivity of clay loam soil (K)
3. Porosity of clay loam soil (ϕ)
4. Rain Leaf Area Index multiplier (Rj)
5. Field capacity of clay loam soil (θ_{fc})
6. Wilting point of clay loam soil (θ_{wp})
7. Understory minimum resistance of crop land ($URsmin$)

The model is not as sensitive to the parameters of the other soil types and land use, because crop lands and clay loam dominate the area of the Jinhua river basin, as can be seen in Figure 4.

The effects of the changes described in Section 3.2 on the mean discharge are visualised in Figure 11. This figure represents the results of a univariate sensitivity analysis where the different parameters are changed individually. This way the effect of a parameter on different objectives can be analysed, in this case the mean discharge. The parameter that is represented by a line with a steeper slope has more impact on the mean discharge, because the change in value of the the mean discharge is higher for the same change in parameter value in terms of percentage.

When looking at Figure 11 it is visible that the rain LAI multiplier (Rj), the field capacity (θ_{fc}), the wilting point (θ_{wp}) and the understory minimum resistance ($URsmin$) have a relatively large effect on the mean discharge. Especially the rain LAI multiplier and the field capacity affect the mean discharge greatly.

4.2.2 Model performance

To see how the parameter values influence the performance of the model as a result of their relative change, the NS and PBIAS are used. First, this is done for the entire discharge series. The results for this can be seen in Figure 12. In this figure it is visible that the rain LAI multiplier (Rj) causes the largest change in the NS and PBIAS, just as it did with the average discharge. The wilting point (θ_{wp}) and the field capacity of clay loam (θ_{fc}) seem to have a larger effect on the PBIAS-value of the discharge, but they also affect the NS-value. The porosity of the clay loam (ϕ) has a large effect on the NS-value, while it relatively does not change as much as the rain LAI multiplier. The understory minimum resistance (URsmin), on the other hand influences the value of the PBIAS more than that of the Nash Sutcliffe coefficient.

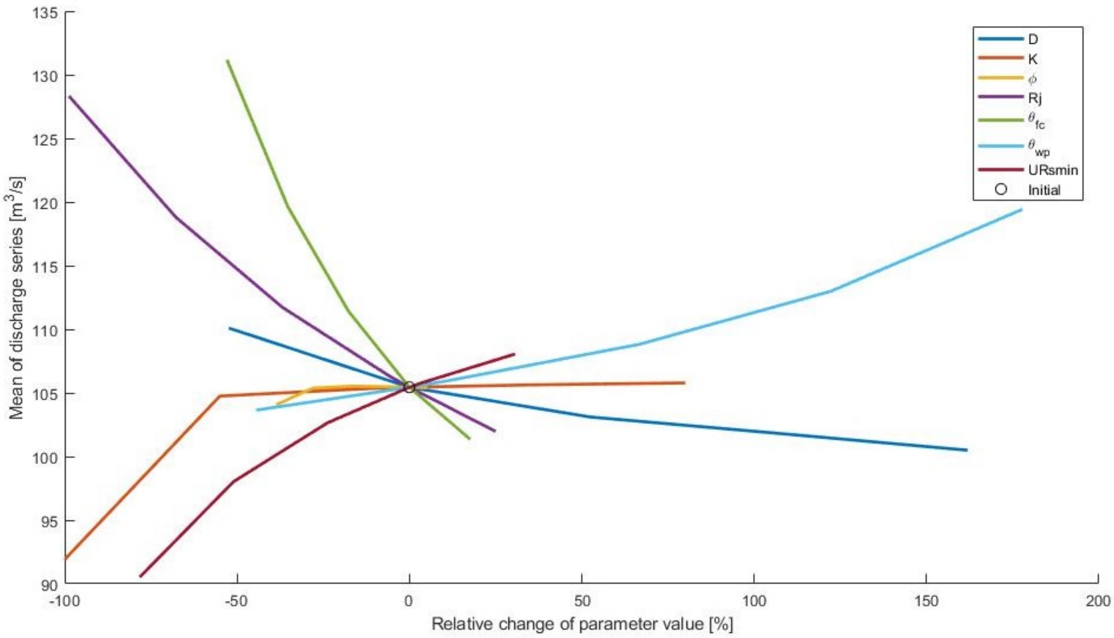
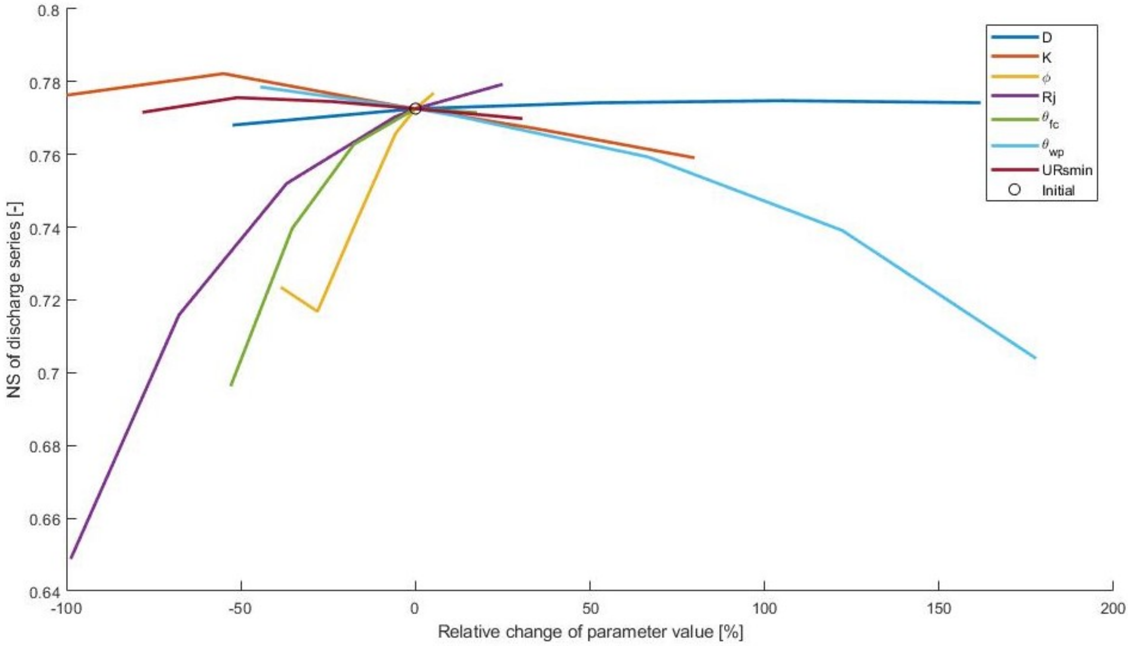


Figure 11: The change in the mean discharge as function of the relative change in parameter values. Circle indicates the initial values

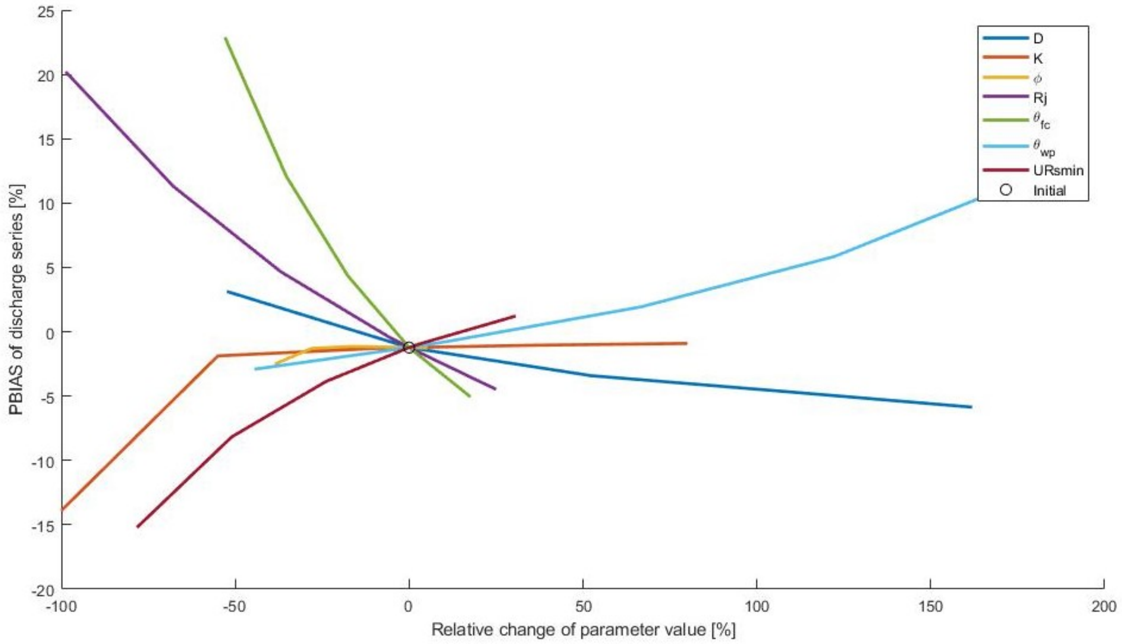
Most of these parameters affect the storage ability of the soil in some way. The porosity influences the storage capacity of the soil directly. The wilting point and field capacity describe the mobile water in the root zone of the soil. These parameters affect the evapotranspiration and thus the water balance with consequences to the water storage and discharge. The rain LAI multiplier, however, influences the amount of water that actually reaches the ground due to interception and can therefore infiltrate or become run off.

After analysing the effect of the parameters on the entire discharge series, the model performance is also analysed for independent peak flows by calculating the NS and PBIAS. This is visualised in the same way as has been done for the entire discharge time series, and can be seen in Figure 13. Here again the same parameters have a high influence on the model performance. However, the understory minimum resistance (URsmin) now seems to have a higher influence on the NS-value, than it did in the discharge series. Also the lateral conductivity has a larger effect on the model performance for peak flows than it does on the entire discharge series.

Comparing Figures 12 and 13 a irregularity is noted. When looking at the course of the PBIAS for the entire discharge series it suggests that there is enough water in the system to cause peak discharges, since the value is both positive and negative. In other words, there is a surplus or shortage of water. The value of the PBIAS for the peak discharges is always negative. This result suggests that there is not enough water to account for the observed peak discharge

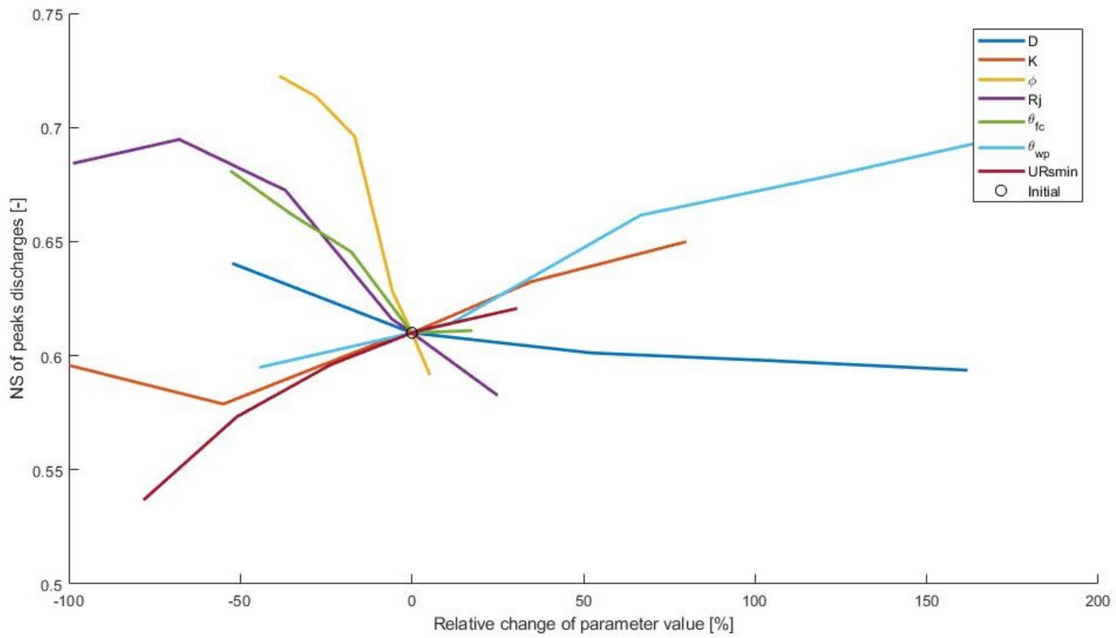


(a) Model performance for discharge series expressed in NS value as function of the relative change in parameter values

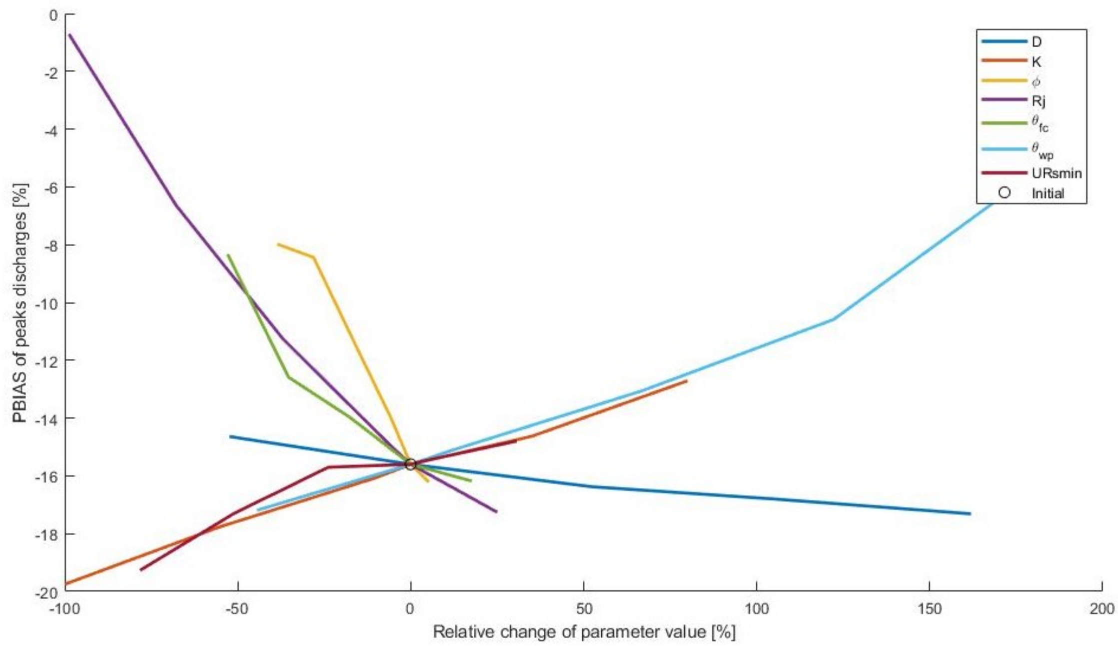


(b) Model performance for discharge series expressed in PBIAS valueas function of the relative change in parameter values

Figure 12: The change in model performance for discharge series as function of the relative change in parameter values. Circles indicate the initial values



(a) Model performance for peak flows expressed in NS value as function of the relative change in parameter values



(b) Model performance for peak flows expressed in PBIAS value as function of the relative change in parameter values

Figure 13: The change in model performance for peak flows as function of the relative change in parameter values. Circles indicate the initial values

4.2.3 Conclusion

In this section the research question to be answered is: What is the effect of parameter estimation on peak flow simulation? From the above it can be concluded that the parameters influence the discharge and model performance for the entire discharge time series and peak discharges, which was expected. The parameters, however, influence the discharge simulation to a lesser extent than the precipitation did, since the slope of the graphs is steeper for precipitation than for the parameters. The parameters that influenced the (peak) discharge simulation most are the porosity (ϕ), rain LAI multiplier (Rj), the field capacity (θ_{fc}), the wilting point (θ_{wp}) and the lateral conductivity (K). Most of these parameters have an influence on the storage of the soil in some way. The modelling of the peak discharges can probably be improved through more extensive calibration, which focusses on the storage capacity of the soils.

4.3 Improving current model results

This paragraph will discuss the results of the steps undertaken to improve the model performance. To start with, the systematic measurement errors that are still present in the currently used data shall be removed. After this more meteorological stations shall be added to the model which will increase the rainfall representation of the, amongst other things, precipitation data. Finally, an attempt has been made to improve the model through parameter optimisation. The section will end with a conclusion giving the answer to the research question addressed in this section.

4.3.1 Removing measurement errors

In Figure 14 the hydrograph before and after the correction of the precipitation data is shown, together with the observed values. This shows that all the simulated discharges have increased compared to the uncorrected data. This makes sense, since the input data of the precipitation has been increased through measurement error correction. At some moments this means that the peaks are closer to the observed discharge, or even more or less equal to the observed discharge. In other cases the peaks are overestimated while the initial state was already very close to the observed peaks. Lastly, it is visible that at some points the peaks were already overestimated by the uncorrected data, so the correction of the data, and with that the increase of precipitation, the peaks are now even more overestimated.

Table 5: Model performances for (peak) discharges after precipitation correction

	Nash-Sutcliffe	PBIAS
Discharges		
Initial	0.77	-1.2 %
Corrected	0.72	10.2 %
Peak discharges		
Initial	0.61	-15.6 %
Corrected	0.75	-7.0 %

Table 5 contains the values of the model performance belonging to Figure 14. It compares the corrected and uncorrected (initial) data for the entire discharge series as well as the peak flows. It can be seen that for the entire discharge series the model performance goes down. Mostly because the low flows were already reasonably well simulated and with the increase of

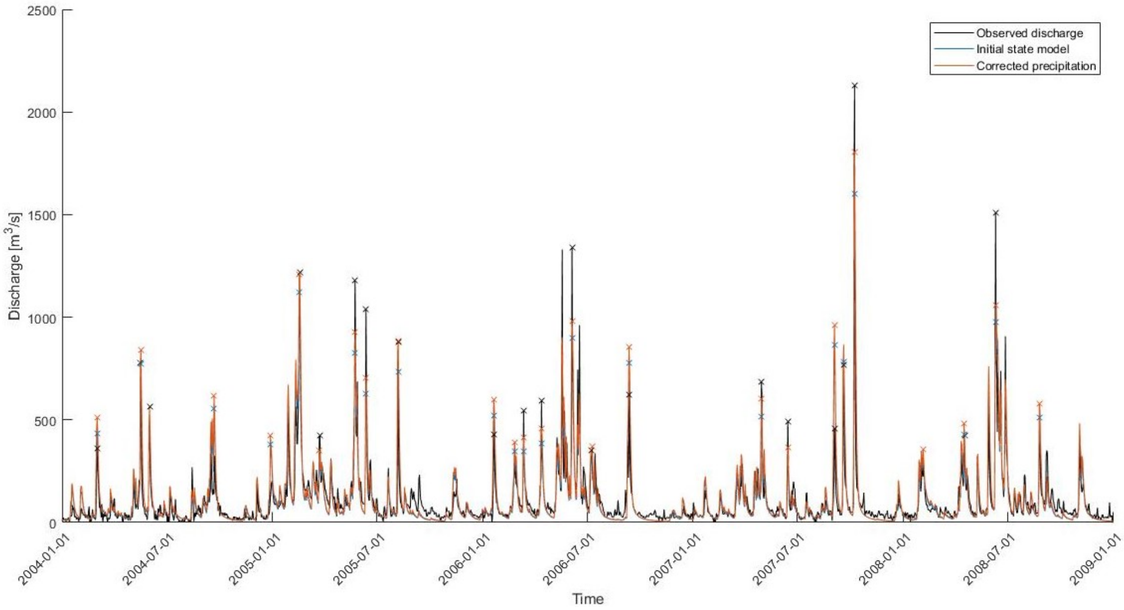


Figure 14: Simulated discharge after precipitation correction. Crosses indicate the peak flows

precipitation they are now overestimated. This is mostly visible in the PBIAS that indicates now a general overestimation of the simulated discharge after correction instead of an underestimation as it did before the correction of the precipitation data. This means that where there was a slight shortage of water in the initial state of the model, there is now a surplus of water in the model of approximately 10.2%. When merely looking at the peak flow simulation the model performance increases. According to the PBIAS value there is still an underestimation of the peak flows using the corrected precipitation data, however it is more than halved compared to the uncorrected data.

4.3.2 Introducing more meteorological stations

To further improve the model performance the rainfall representation of the precipitation data has been increased through adding 16 additional meteorological stations. While preparing the data for the model it came to notice that the variable values of the same station that were present in both data sets differed from each other. The cause of this is most likely that the second data set was aggregated differently than the first data set. The first data set was hourly data aggregated from 8pm until 8pm the next day. However, the second data set was hourly data aggregated from 12am until 12am the next day. Another discrepancy was found in the definition of Jinhua meteorological station in the model. The elevation that was defined there was approximately 10 meters higher than the elevation that was provided in the second data set. When comparing the generated discharges it was visible that this did have a slight effect. From this point onwards the second dataset will been used as leading. Also the available time period has changed from 2004-2008 to 2006-2008.

In Figure 15 the result of the model run for the initial state, the corrected data for five stations and the inclusion of the 16 other stations, that were also corrected, are visualised. Also the observed values are added into the plot. From this it is already visible that the simulated discharges with 21 stations are lower than those of the other simulations. For some peaks this results in a better match, but mostly the peaks are even more underestimated. With regard to

Table 6: Model performance after implementing additional stations

	Nash-Sutcliffe	PBIAS
Discharges		
Initial (uncorrected 5 stations)	0.58	1.0 %
Corrected 5 stations	0.50	11.7 %
Corrected 21 stations	0.77	-18.1 %
Peak discharges		
Initial (uncorrected 5 stations)	0.70	-10.7 %
Corrected 5 stations	0.74	-3.3 %
Corrected 21 stations	0.47	-23.6 %

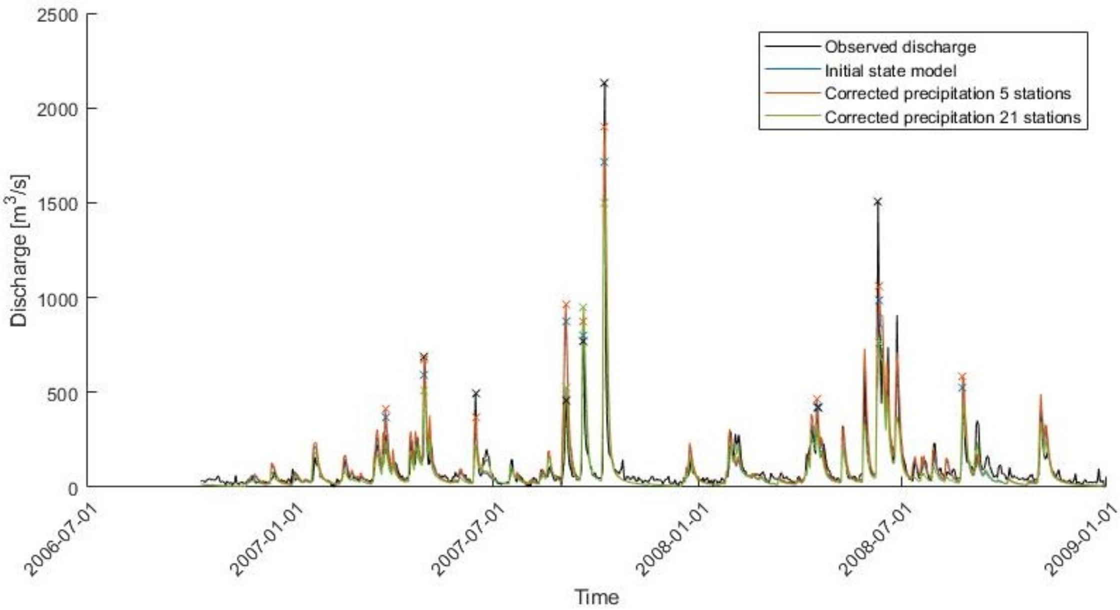


Figure 15: Simulated discharge after the addition of 16 meteorological stations. Crosses indicate the peak flows

the entire hydrograph, there is a general underestimation of the flows. This is also clear when looking at the PBIAS values of the model with 21 meteorological stations, given in Table 6. However, for the entire discharge series the Nash-Sutcliffe coefficient improves drastically.

Since the current model is calibrated using five meteorological stations and no correction for systematic measurement errors, the model should be recalibrated to actually improve the model performance. This process will be elaborated on in Section 4.3.3.

4.3.3 Model parameter optimisation

The final step of improving the model is changing the parameter optimisation. For the optimisation 5 parameters were taken into account found in Section 4.2. These parameters are the rain LAI multiplier (Rj), porosity (ϕ), lateral conductivity (K), field capacity (θ_{fc}) and the wilting point (θ_{wp}) of the clay loam soil. The ranges of possible parameter values were based upon the ranges found in Pan et al. (2017). However, there are some constraints to the parameter ranges, since the porosity cannot be smaller than the field capacity, and the field capacity in its turn cannot be smaller than the wilting point (S. Pan, personal communication, May 2, 2018). The ranges are set in such a way that the above cannot happen in any case. After the algorithm has finished with the optimisation the ranges will be adjusted based on the results of the first calibration iteration. The parameter value ranges for the optimisation iterations can be found in Appendix C. After five iterations of the calibration it was concluded that the objective functions were reasonably stable and the optimum parameter values at that point were used for the validation. After the calibration it became clear that compared to the initial state some of the parameters had been changed, that were not taken into account for the calibration. This made the comparison between the initial state and the calibrated situation unfair. However, due to the limited time after this discovery it was decided to not redo the calibration. Instead, to make a fair comparison to the initial state of the model, the choice was made to adjust parameter values that were unintentionally changed during calibration in the initial state. This way the effect of the precipitation and parameter estimation could still be analysed.

In Figure 16 the result of the calibration for 5 and 21 stations in the calibration period is visualised, together with the initial state of the model during the calibration period. It can be seen from this figure that compared to the initial state of the model the calibrated model with 21 stations greatly improves the discharge simulation at some point. At other points the discharge is overestimated while it was not the case in the initial state. The peak flows seem to be simulated better and are in general closer to the observed discharges. However, the largest peak that occurs in this time period is still greatly underestimated. On the other hand it is better than the initial state of the model. The model improves less when comparing it to the situation with the 5 corrected stations. Most peaks have a similar value, only the two peaks just before October 2007 differ greatly. The first peak is more accurate in the situation with 21 stations and the second peak is overestimated in the situation with 21 stations and underestimated in the situation with 5 stations. The model with the 5 corrected stations is in that case more accurate. When looking further at the hydrograph it is visible that the model also has some issues with the small variations that occur in the lower flows. Even though the model with 21 stations also has some issues in with the small variations, especially from October 2007 until December 2007, it seems to perform better during these lower flows than the model with 5 stations.

Table 7 contains the model performance that belong to Figure 16. The NS and PBIAS have been calculated again for the entire discharge series. Also for the peak discharges the calculation was done again, despite that there are only four independent peaks present in this period. It should be noted that especially for the peak flows these values cannot be used to draw solid conclusions from. They are only presented for a complete picture. The model performance in this period has been drastically improved compared to the initial state of the model and also compared to the non-calibrated model which is quantified in Table 6. Compared to the calibrated model with 5 stations the improvement is less significant. For both the peak discharges and the entire discharge series the NS value stays the same and the PBIAS value only decreases slightly with 5 percent points when introducing the additional stations.

The hydrograph of the validation period is visualised in Figure 17 with the quantification in Table 8. From the hydrograph it is visible that at some points the simulated discharge from the model with 21 stations improves compared to the initial state of the model. However, improvement is less visible than during the calibration period. The simulation of peak discharges also improves, although it remains difficult to correctly predict the highest peak flow, which is still greatly underestimated. Compared to the model situation with 5 corrected stations the improvement is not really visible for the peak discharges. In both cases the peak flows remain underestimated, the model situation with 21 stations even has a larger underprediction than that with 5 corrected stations. Again the model has trouble with the variations that are observed in

Table 7: Model performance after calibration in the calibration period

	Nash-Sutcliffe	PBIAS
Discharges		
Initial (uncorrected 5 stations)	0.77	-24.1 %
Corrected 5 stations	0.80	-7.5 %
Corrected 21 stations	0.80	-2.5 %
Peak discharges		
Initial (uncorrected 5 stations)	0.59	-23.0 %
Corrected 5 stations	0.77	-13.0 %
Corrected 21 stations	0.77	-8.5 %

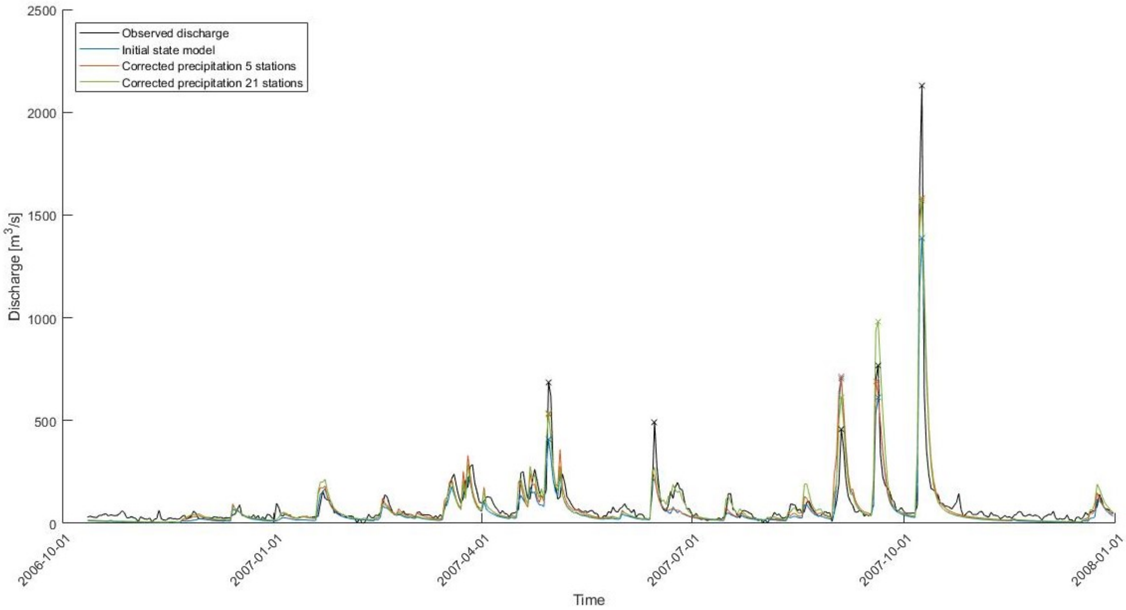


Figure 16: Simulated discharge after calibration in the calibration period. Crosses indicate peak flows

the lower flows . However, in this case the model situation with 21 stations does not necessarily improves in this, as it did do during the calibration period.

The fact that the model improvement is not really present in this period is also visible in the NS and PBIAS values in Table 8. The model performance values are a little better for the model with 21 stations than for the initial state of the model with regard to the peak flows. However, compared to the calibrated model with 5 meteorological stations there is even a decline in the model performance, for both the peak discharges as the entire discharge series. In general the performance is poor in this period. Since there are only two peak discharges in this period again it must be noted that conclusions with regard to the peak flows cannot be drawn from this.

To make an easy comparison between all the different model situations and the corresponding model performance all the NS and PBIAS values are summarised in Table 9. It is clear that based on these model performance indicators there is an improvement compared to the initial state of the model. However, between the 5 corrected stations and the 21 corrected stations this improvement is hardly present. This contradicts the hypothesis that with a better representation of rainfall throughout the area the model will perform better. In Section 2.4.2 a table is given

Table 8: Model performance after calibration in the validation period

	Nash-Sutcliffe	PBIAS
Discharges		
Initial (uncorrected 5 stations)	0.75	-27.0 %
Corrected 5 stations	0.76	-21.0 %
Corrected 21 stations	0.74	-21.7 %
Peak discharges		
Initial (uncorrected 5 stations)	0.18	-39.3 %
Corrected 5 stations	0.26	-35.2 %
Corrected 21 stations	0.22	-37.6 %

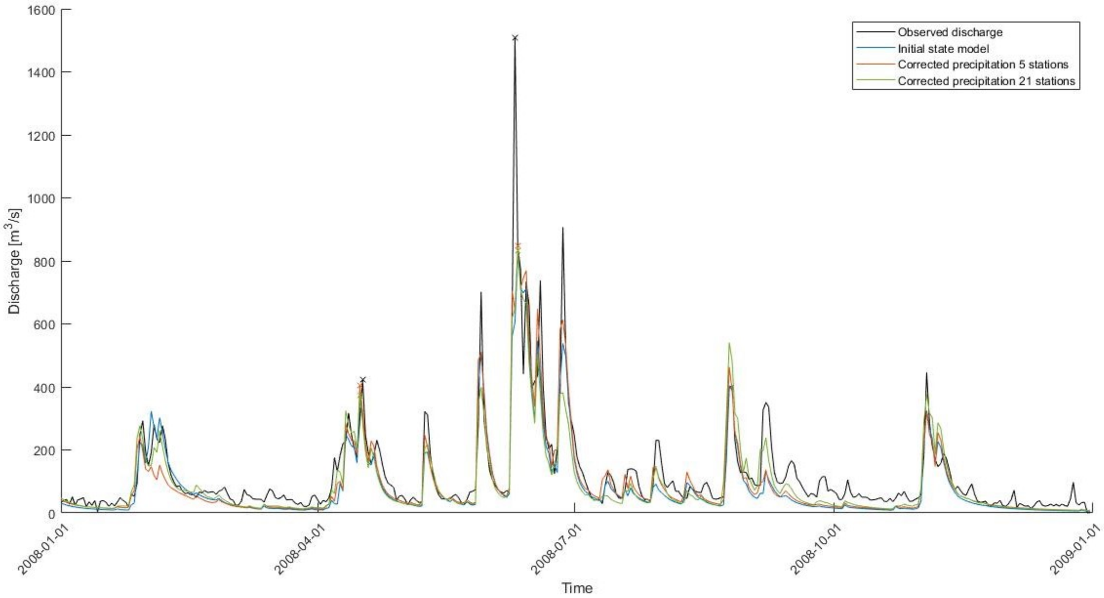


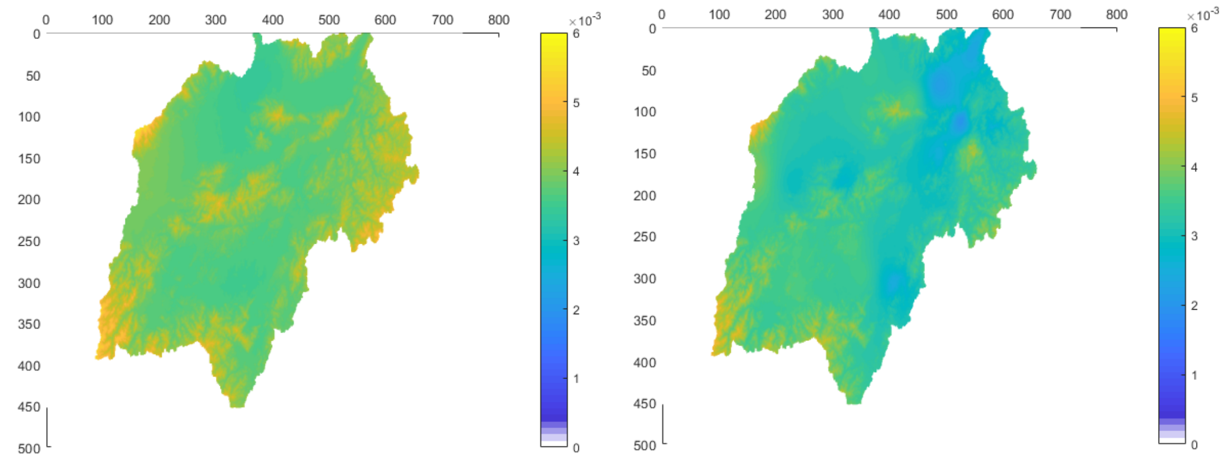
Figure 17: Simulated discharge after calibration in the validation period. Crosses indicate peak flows

providing the total amount of measured precipitation in 2008 per station. It is visible that the 5 initial stations measured precipitation amounts well above 1200 mm, while the other stations also measured precipitation amounts in that year below 1000. The model interpolates and extrapolates the measured precipitation. The outcome of this is bound to be influenced when additional data points are added, and since the additional data points used here mostly provide lower precipitation there is a high chance that the total interpolated precipitation is also lower. To see the effect of this a small cross-validation is done by using the inter- and extrapolated values of the model when using only 5 stations to see if it matches the precipitation that was measured at the locations of the other 16 stations. This is done using the total precipitation in 2008 and the results of this are visualised in Figure 18. It turned out that the measured precipitation is lower than the model interpolated using the 5 station data. The total amount of precipitation over the entire area that the model outputs using 5 stations compared to the 21 stations is also higher. Which is a logical explanation why the simulated peak discharges do not increase as much as might be expected and are even more underestimated.

Furthermore, the PBIAS values suggest there is structurally too little water compared to the real world. This can be because of the stage-discharge relationship that is used by the hydrological bureau to determine the discharges. Higher flows are often unreliable because the linear relationship used is not applicable for higher flows in the field (T. Rienjes, personal communication, July 16, 2018). These relations should be updated each year to guarantee the correct output. However, not much is known about the stage-discharge relationship, since the Bureau of Hydrology directly provides the discharges and nothing else.

Table 9: Overview model performances for the different model situations and time periods

	NS		PBIAS	
	Discharges	Peak discharges	Discharges	Peak discharges
Initial (uncorrected 5 stations)				
2004/2008	0.77	0.61	-1.2%	-15.6%
2006/2008	0.58	0.70	1.0%	-10.7%
2006/2007	0.77	0.59	-24.1%	-23.0%
2007/2008	0.75	0.18	-27.0%	-39.3%
Corrected 5 stations				
2004/2008 (before calibration)	0.72	0.75	10.2%	-7.0%
2006/2008 (before calibration)	0.50	0.74	11.7%	-3.3%
2006/2007 (calibration period)	0.80	0.77	-7.5%	-13.0%
2007/2008 (validation period)	0.76	0.26	-21.0%	-35.2%
Corrected 21 stations				
2004/2008	-	-	-	-
2006/2008 (before calibration)	0.77	0.47	-18.1%	-23.6%
2006/2007 (calibration period)	0.80	0.77	-2.5%	-8.5%
2007/2008 (validation period)	0.74	0.22	-21.7%	-37.6%



(a) Network with 5 stations

(b) Network with 21 stations

Figure 18: Mean precipitation in 2008 per grid cell in meters

4.3.4 Conclusion

The goal of this section was to improve the model performance, with a focus on the peak discharges. This was firstly tried by correcting the precipitation data for structural measurement errors. This had an effect on the simulated discharges, and with respect to the peak discharges the model performance improved. However, for the entire discharge series the model performance decreased. After this the effect of an increased representation of the precipitation data was examined. The difficulty was that the time period was decreased, due to the limited available data from the additional stations and missing observed discharges after 2008. After the implementation of the additional stations the model performance was assessed again. Although the value of the Nash-Sutcliffe coefficient improved over the entire discharge series the PBIAS value decreased. The model performance with a focus on the peak discharges decreased drastically compared to the situation with five meteorological stations. Therefore it was chosen to perform a calibration procedure using an automatic genetic calibration algorithm with three objectives, where the five parameters that were found to affect the peak discharges most were taken into account. This was done for the situation with corrected precipitation for 21 stations as well as for 5 stations to make the results more comparable, since a new objective has been added. After the calibration it turned out that for both models the performance increased drastically compared to the initial state in the calibration period. However the model with 21 meteorological stations did not improve greatly compared to the one with 5 meteorological stations, although there was a slight improvement in the PBIAS value in this period. For the validation period the model performance increased slightly for the two calibrated models compared to the initial state of the model. The performance did not improve when comparing the model with 21 stations to the model with 5 stations, it even declines. This is possibly due to the interpolated precipitation that is too high when using 5 stations.

5 Discussion

The results in the previous chapter have shown that precipitation is an important variable in peak flow simulation and also parameter estimation plays an important role. The change in precipitation data input, the representation of it as well as the correction of measurement errors, have changed the model performance. To further improve the model a small calibration has taken place. This chapter will reflect on the taken steps in the research and the results and will relate them where possible to the literature. Besides this it will be discussed what the potential as well as the limitations of this research are.

5.1 Reflection

The study that was performed can be divided into two parts. First the influence of the precipitation and parameter estimation on the (peak) discharge simulation were individually investigated. Based on these results an attempt was made to improve the model performance as a second part of the research. This was supposed to be achieved by increasing the representation of the precipitation data and parameter optimisation. The increase in rainfall representation was achieved through the implementation of 16 additional meteorological stations. However, even after optimisation no clear improvement was visible. This raises the question why the inclusion of more stations does not change the model performance for the better. The most probable reason for this is that the spatial variability of the precipitation in this area is not captured with this number of stations and more stations are needed to capture this. When looking at Figure 5 and Table 3 in Chapter 2 it is visible that all the stations are located close to the river and the elevations of the stations vary from 62.5 to 466 meter with an average of 155 meter, while the entire area has elevations that go up to almost 1300 meter and has an average of 254 meter. This means that especially precipitation patterns at higher elevations are not well represented and it is therefore not known how the precipitation responses when the elevation increases. The spatial variability plays an even more important role when it comes to the simulation of peak discharges. The question is then: what is the spatial variability of the precipitation and what are the number of stations necessary to capture this variation? In an area where there is little spatial variation, such as a field, a rain gauge can be representative for a larger area than in a mountainous area where there is a larger spatial variation. This study area lies in a mountainous region, so the spatial variability of precipitation will probably be large. The exact spatial variability of precipitation in this area cannot be determined using the data that is available now. The variability can be based on areas that are similar to this study area. Dong et al. (2005) tried to identify the appropriate number of rain gauges in a catchment using the lumped model HBV. They showed that the correlation between the mean areal precipitation and discharge increases hyperbolically with the increase in number of gauge stations until a critical number of rain gauges, after which it levels off. The number of critical gauge stations was found to be five for their study area, the Qingjiang river basin. Both the Qingjiang and the Jinhua river basin have a subtropical climate and consists of a mountainous area. However, the range in elevation in the Qingjiang river basin is larger and the total surface area is almost three times the size of the Jinhua river basin. The World Meteorological Organisation (2008) states that the density of rain gauges should be between 250 and 575 km^2 per station for mountainous areas. Arsenault and Brissette (2014) tried minimizing the number of gauges while maintaining a good model performance. They performed their study in the Toulnustouc river basin in Québec, Canada. This is a hilly to mountainous catchment that has a continental climate (Gouvernement du Québec, 2018). Although the climate is different from the Jinhua river basin, the size of the two basins is more comparable. Arsenault and Brissette (2014) found that for the Toulnustouc river basin the optimal density of gauge stations is between 1600 and 4000 km^2 per station, which corresponds to two to five stations in their catchment. They do note that although two or three stations would suffice, the optimal number of stations is four or five. Both Arsenault and Brissette (2014) and Dong et al. (2005) used a lumped model in their studies, while this study used a distributed model. Whether this makes a difference in the optimum density is not found.

5.2 Limitations

There is one obvious limitation in this research, the data quantity. This resulted in a limited period for calibration and validation. This limitation will be addressed in this section together with the precipitation lapse rate and calibration and validation.

5.2.1 Data quantity

The meteorological data used in this study was acquired from two different data sets and not all the necessary variables for the model were measured at all stations. Also the temporal scale differed for the different stations. The stations that were initially used provided daily data, however the additional stations had hourly meteorological data. Since the current model is a daily model and the time was too limited to change the model to an hourly model, the choice was made to aggregate the hourly data to daily data. Furthermore, the additional stations missed the measurements of sunshine hours, which are required for the calculation of a model input: the long and short wave radiation. This affects the evapotranspiration that occurs during the day in the area. To solve this the available sunshine hours from the five initial stations were used and interpolated to the coordinates of the stations where these were not available, even though this introduces an error into the model. The interpolation technique used was the nearest neighbour technique, because the usage of other interpolation techniques resulted in NaN-values. A number of studies has been done to investigate what the effect of evapotranspiration is on discharge simulation, also Andréassian et al. (2004) and Oudin, Michel, et al. (2005a) investigated this. They both found that in terms of model efficiency a simple assumption on potential evapotranspiration in a watershed does not yield more accurate results in discharge simulation. Oudin, Michel, et al. (2005a) state that these results bring into question whether a detailed knowledge of evapotranspiration is necessary for rainfall-runoff modelling. Andréassian et al. (2004) raises this question as well, although they note that additional research is necessary. Oudin, Hervieu, et al. (2005b) further investigated the need for detailed evapotranspiration in a model. They proposed a temperature-based PE model, which only requires the mean air temperature. This new model leads to a slight improvement in rainfall-runoff model efficiency. So, even though the small error in evapotranspiration that was introduced in this study, it will probably not have the largest effect on the results of the study. If a more accurate evapotranspiration is desired the model proposed by Oudin, Hervieu, et al. (2005b) can be used.

Four meteorological stations were available in both data sets: Dongyang, Jinhua, Yiwu and Yongkang. While preparing the data from all the meteorological stations it came to notice that the measured variables at the common stations slightly differ from each other at the same date. This might be explained by the different ways of aggregation that were used in both datasets. The first data set contained data that was aggregated by the hydrological bureau, which aggregates the data from 8 pm until 8 pm the next day. The second data set was aggregated by Suli Pan, who did this from 12 am until 12 am the next day. When looking at the daily variations in a subtropical climate in the Eastern part of China it is visible that precipitation falls in two peaks: early morning and late afternoon (Yuan et al., 2012). The choice of aggregation method has an impact on the amount of precipitation that falls at any given day in the model. Peak flows will respond stronger to this difference than low flows, since the peak flows are generated by larger and shorter precipitation events.

5.2.2 Precipitation lapse rate

As pointed out in Section 5.1 it is important to obtain more measurements at a wider variation of elevations to determine the spatial variability of precipitation. Besides this, it is also of importance to determine the appropriate precipitation lapse rate. Momentary the value of the lapse rate is based on calibration that took place in a previous study (Pan et al., 2017) and the simplest linear precipitation lapse rate formula is used, which is not common practice. Although Liston and Elder (2006) proposed a non-linear lapse rate formula for precipitation, the formula is not changed, since the precipitation lapse rate is dependent on many geographic factors and little is known of how the precipitation responds to elevation in this area. When this is unknown it is best to use the most simple equation (M. Booij, personal communication, April 5, 2018). However, the lapse rate is a measurable variable which can be determined based on precipitation measurements. It might be possible that in this area the precipitation lapse rate is not a linear relationship as is used now. To make this fit the reality better it is necessary to use measurements of a wider variation of elevations than are now available. The discharge stations that are now available do not provide data at higher elevations, it is therefore necessary to use other sources of data, such as satellite or radar. These types of precipitation data might also be able to capture the spatial variability of the precipitation better than the currently used meteorological stations.

5.2.3 Calibration and validation

The model used in this research is a distributed model which requires quite extensive data input. The gathering of the data is a difficult job, especially with a high resolution. For this research data from 24 different meteorological stations was available for varying time periods. This made the overlapping time period for all the stations limited. Combined with the even more limited available observed discharges the total period that could be used for all 24 stations was one year. Excluding three stations resulted in approximately 2.5 year of usable data for calibration and validation. Calibration took place from August 2006 until December 2007 and validation took place from January 2008 until December 2008. Although in other studies calibration with such a short time period has been done before (Brown et al., 2013; Sun et al., 2016), it is not desirable and it would be better if more data for calibration and validation was available. Perrin et al. (2007) did a study to the minimum number of data points necessary to perform a calibration in case a time series is not continuous. They found that 350 calibration days sampled out of a longer data set including dry and wet conditions are sufficient to obtain robust estimates of model parameters. In this study the calibration consisted of 426 consecutive days, so all seasons were taken into account during calibration. Another issue that was raised due to this short calibration and validation time was the small number of peaks that was available to assess if the model performance had improved with regard to peak flows. The calibration period consists of only four independent peaks and the validation period even less, namely two independent peaks.

This calibration has been performed using five parameters that the peak flow was found to be most sensitive to in Section 4.2. However, this sensitivity analysis only included the parameters that the entire discharge series was found to be sensitive to, according to a previous study (Pan et al., 2017), and not specifically for peak flows. It might be possible that the peak flows are more sensitive to other parameters, such as those related to surface run off generation, that are not taken into account in this research. The reason for the less extensive sensitivity analysis is mainly the limited amount of time that was available.

5.3 Potential

This study confirmed that the precipitation is an important factor in the discharge simulation in the Jinhua river basin using DHSVM, although the increase in rainfall representation did not give results that were expected. That more meteorological stations do not necessarily result in better discharge simulation has been shown in other studies as well (Arsenault and Brissette, 2014; Dong et al., 2005). Both these studies were performed in a mountainous area with lumped models. The type of climate and catchment size differed in these studies, which shows that these results are generic for mountainous areas despite their climate. This study adds to these results, having the climate in common with Dong et al. (2005) and having the catchment size in common with Arsenault and Brissette (2014). This study does differ in the type of model used, which gives a new insight in the topic that also for distributed models more gauge stations does not necessarily give a better discharge simulation. However, Arsenault and Brissette (2014) and Dong et al. (2005) also investigated the placement of the stations and concluded that this was of great importance. Arsenault and Brissette (2014) used a virtual gauge network and was able to place stations at specific useful locations such as the areas where spatial and temporal coverage was lacking. They acknowledge that in the real world it is not always possible to locate stations wherever it is desired, but it is worth to sometimes choose more remote locations.

Even though there was no improvement in the model performance, the methods used in this study are easily applicable in similar studies to the effect of a natural phenomenon on discharges, whether these are peak discharges, low flows or discharges in general. The sensitivity analyses done are basic, but give an understanding of how the study area and model respond to changes in the precipitation and the parameter values. Which helps in determining effective ways to improve hydrological models. However, certain phenomena and parameters also influence each other. So for a full understanding of the situation a more extensive analysis should be performed.

6 Conclusions and recommendations

In this chapter the conclusions that can be drawn from the results are given. The answers to the research questions regarding the influence of precipitation and parameter estimation on the simulation of peak discharges will be given in Section 6.1, as well as the conclusions regarding the improvement of the model through increasing the rainfall representation of the data and model calibration. After this the recommendations that come from this study are given in Section 6.2.

6.1 Conclusions

There were three research questions addressed in this study that aimed to fulfil the objective that was set for this research. The conclusions in this section will be given first per research question, and after that some general conclusions that can be drawn are given.

6.1.1 Influence of precipitation data on (peak) discharge simulation

It has become clear that the precipitation data that is currently used has been cleared of measurement errors due to failure of equipment. Also, the model already corrects for height when interpolating the precipitation. However, structural errors in the measurements such as wind induced errors and, wetting and evaporation loss are not corrected for. This correction might help to improve the simulation of peak discharges. Furthermore the relation between precipitation and (peak) discharges was examined. It was found that precipitation correlates with discharge in a non linear way. When the precipitation was changed with 10%, the discharge changed with almost 20%. It was also visible that the precipitation and discharge peaks occurred around the same time, which indicated that there is a relation between the two physical quantities. The relation between the precipitation and peak discharges was examined through a correlation assessment that varied the time lag and temporal scale of the precipitation to find what combination of these two caused for the highest correlation. It turned out that for a temporal scale of 8 days and a time lag of 2 days, the correlation between peak discharge and precipitation was at its highest (R=0.93). This high correlation coefficient and the way discharge simulation changes when precipitation is increased, indicated that the precipitation has a significant influence on (peak) discharge simulation and it is worthwhile to use the precipitation data in a way to improve the model performance.

6.1.2 Influence of the model on (peak) discharge simulation

The influence of the parameters is identified through a univariate sensitivity analysis with seven parameters that were chosen based on the results of the two step sensitivity analysis performed by Pan et al. (2017). The model was most sensitive to five of these seven parameters. The parameters that influenced the (peak) discharge simulation most are the porosity (ϕ), rain LAI multiplier (Rj), the field capacity (θ_{fc}), the wilting point (θ_{wp}) and the lateral conductivity (K). Most of these parameters have an influence on the storage of the soil in some way. The largest sensitivity in the mean discharge was by the field capacity, where a change of 50% in the parameter value caused around 30% change in mean discharge. For the effect on the peak discharges the model performance was examined in terms of the Nash Sutcliffe coefficient and PBIAS value. These model performance indices measure to which extent the model simulates the observed values correctly and if the observations are under- or overestimated. The effect of the parameters on the peak discharge is similar to that on the mean discharge. It can be concluded that the parameters influence the discharge and model performance for the entire discharge time series and peak discharges, which was expected. However, the parameter estimation does not have as large an effect on the discharge simulation as the precipitation had.

6.1.3 Improving current model results

Improving the model performance, with a focus on the peak discharges was firstly tried by correcting the precipitation data for structural measurement errors. This had an effect on the simulated discharges, and with respect to the peak discharges the model performance improved. However, for the entire discharge series the model performance decreased. After this the effect of an increased representation of the precipitation data was examined. The difficulty was that the time period was decreased, due to the limited available data from the additional stations and missing observed discharges after 2008. After the implementation of the additional stations the model performance was assessed again. Although the value of the Nash-Sutcliffe coefficient improved over the entire discharge series the PBIAS value decreased. The model performance with a focus on the peak discharges decreased drastically compared to the situation with five meteorological stations. Therefore it was chosen to perform a calibration procedure using an automatic genetic calibration algorithm with three objectives, where the five parameters that were found to affect the peak discharges most were taken into account. This was done for the situation with corrected precipitation with 21 stations as well as 5 stations to make the results more comparable, since a new objective function has been added. After the calibration it turned out that for both models the performance increased drastically compared to the initial state in the calibration period. However the model with 21 meteorological stations did not improve greatly compared to the one with 5 meteorological stations, although there was a slight improvement in the PBIAS value in this period. For the validation period the model performance increased slightly for the two calibrated models compared to the initial state of the model. The performance did not improve when comparing the model with 21 stations to the model with 5 stations, it even declines. This is possibly due to the interpolated precipitation that is too high when using 5 stations.

6.1.4 General conclusions

The main objective of this study was to find the effect of precipitation and parameter estimation on simulating the peak discharges in the Jinhua river basin using DHSVM. This was done with the goal to improve the discharge simulation with a special focus on the peak flows. It was found that the precipitation was the most important factor in the simulation of the discharge. By increasing the density of the precipitation network, together with the calibration of five parameters, an attempt was made to achieve an improvement of the simulation of peak discharges. Even with a higher density of the precipitation network, the peak discharge simulation did not improve. An explanation for this might be the interpolation of the precipitation throughout the area. The measured precipitation of the 16 additional stations was on average lower than that of the 5 initial stations. This made for a total precipitation throughout the entire study area that was lower when the extra stations were added to the model.

6.2 Recommendations

Based on the above discussion and conclusions several recommendations are formulated. First, the sensitivity analyses performed in this study have not been extensive enough and were based on an earlier two-step sensitivity analysis on the entire discharge series, due to the limited time. However, it is possible that the peak discharges respond more strongly to other parameters that were not included in the sensitivity analysis performed in this study. Therefore it is wise to do a sensitivity analysis with a focus on peak discharges more extensively in further research.

Secondly, after increasing the representation of the precipitation data through implementing additional meteorological stations into the model, the performance of the model for the peak flows did not increase with this change. A likely explanation for this is that the spatial variability of the study area is not captured and the spatial representation of the precipitation data should be increased further. The question is then how much this should be increased. To answer this question the spatial variability should be determined. This is a difficult task, which requires more measurements. It is also possible that the precipitation lapse rate can be based on known lapse rates in similar areas. Especially the way the precipitation responds to the increase of elevation is not known in this study area. For the improvement of the model there is still much to be won. Other studies also showed that with the right placement of gauge stations the same model performance can be obtained as with a denser gauge network. Therefore the recommendation is to invest in opening meteorological stations that are located on more remote locations, even though this might not always the most convenient location.

Third, the model was calibrated and validated with a limited time period. This was mainly due to the fact that the overlapping observed data, meteorological data and discharges, was limited. There is more discharge data present at the station, however it was not available for this study. If the additional observed discharges would be accessible for future research the calibration and validation of the model could be done more extensively which would help with improving the peak discharge simulation and also the analysis of the model performance with regard to the peak flows. Also, other discharge stations in the study area can be used to see whether the underestimation of peak discharges is a problem in the entire catchment or only at the Jinhua outlet.

Fourth, in the study area there is not a uniformly spread precipitation throughout the year, which causes for high peak flows in the summer and low flows in the remaining of the year. This makes it hard to simulate both these types of discharges correctly. A possible solution for this can be a dynamic model parametrisation, which makes a distinction between the peak flows and low flows. This way the hydrograph can match the peak flows as well as the low flows better to the observations.

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A Model description DHSVM

DHSVM provides a dynamic representation of watershed processes at the spatial scale described by Digital Elevation Model (DEM) data (Wigmosta, Nijssen, and Storck, 2002). The model has evolved since it was first introduced and consists of multiple layers, which all have underlying formulas that need input data. In this appendix a short introduction of the different layers will be given, for a more detailed description refer to Wigmosta, Nijssen, and Storck (2002).

A.1 Evapotranspiration

Wigmosta, Nijssen, and Storck (2002) describes that the evapotranspiration is calculated separately for the overstory and the understory. First the potential evaporation for the overstory is calculated. Water intercepted by the overstory is subtracted from the wet fraction and the transpiration from the dry fraction is calculated using a Penman-Monteith approach. The calculated overstory evapotranspiration is subtracted from the potential evapotranspiration and the understory is calculated from the modified potential evaporation rate. This stepwise approach allows for the overstory to dry during a time step.

A.2 Two-layer ground snowpack model

According to Wigmosta, Nijssen, and Storck (2002) the snowpack is modelled as two layers: a thin surface layer and a lower pack layer. The accumulation of the ground snowpack are simulated using the energy- and mass-balance model of Storck and Lettenmaier (1999) and Storck (2000) (in Wigmosta, Nijssen, et al., 2002). Depending on the presence of an overlayer the snowpack on the underlayer can be determined. The canopy processes follow the same principle as in the evapotranspiration layer of the model.

Since the study area of this research seldom encounters snowfall, this module can be disregarded here (Pan et al., 2017).

A.3 Canopy snow interception and release

This layer of DHSVM uses the canopy snow model described by Storck and Lettenmaier (1999) and Storck (2000) (in Wigmosta, Nijssen, et al., 2002) to represent the combined canopy processes that control snow interception, sublimation, mass release, and melt from the forest canopy.

Since the study area of this research seldom encounters snowfall, this module can be disregarded here (Pan et al., 2017).

A.4 Unsaturated soil moisture movement

The amount of throughfall, snowmelt and surface run off from adjacent cells determine the water that the soil surface receives. The user defines the maximum infiltration rate, which determines the total depth of water that can be infiltrated during each time step. The excess water will be available for surface routing (Wigmosta, Nijssen, and Storck, 2002). The unsaturated moisture movement is modelled using a multi-layer representation based on the two-soil layer model, first introduced by Wigmosta, Vail, and Lettenmaier (1994). The model first calculates the infiltration into the upper layer, then downward vertical moisture transfer. The net flux of lateral saturated subsurface flow is then added to the bottom soil layer and soil moisture is updated for each layer. From bottom to top each soil layer is checked whether the soil moisture is larger than the porosity, if this is true then the excess water will be added to the layer above, eventually resulting in a possible surface run off (Wigmosta, Nijssen, et al., 2002).

A.5 Saturated subsurface flow

DHSVM applies a cell-by-cell approach to route saturated subsurface flow (Wigmosta, Vail, and Lettenmaier, 1994), using either an approximation by local ground surface slopes (kinematic assumption) or by local water table slopes (diffusion assumption). The flow direction of the subsurface flow is assigned through the index k, which is numbered from 0 to 7 in a clockwise direction from the North (Wigmosta, Nijssen, and Storck, 2002). When the subsurface flow crosses a road network and the water table is less deep than the road cut, it will be intercepted by the road. The same goes for when the subsurface flow crosses a channel.

A.6 Overland flow

According to Wigmosta, Nijssen, and Storck (2002), surface run off is generated when: (1) the input of throughfall and snowmelt, exceeds the infiltration capacity set by the user, (2) throughfall or snowmelt occurs on a saturated cell, or (3) the water table rises above the ground surface. In DHSVM there are two methods to route the surface run off. This can be done by an explicit cell-by-cell approach (must be used in case of roads or channels), or by a unit hydrograph approach. The explicit method works in a similar way as the method used for the subsurface flow. The unit hydrograph approach calculates the function for the response time per cell. These functions can consist of a linear translation component as well as a linear storage component.

A.7 Channel flow

The routing of channel flow is done by a relatively simple linear storage routing algorithm. In this each channel reach is treated as a reservoir with a constant width, with outflow linearly related to storage. The constant flow velocity is calculated from Manning's equation (Wigmosta, Nijssen, and Storck, 2002). The flow routing of road drainage ditches and stream channels is more complicated and uses numerous linear channel reservoirs, also allowing for reinfiltration and overland flow routing.

B Adapting the optimisation algorithm

During this research a optimisation algorithm was used written for DHSVM. During the preparation of the code to apply it on this specific case it came to light that the code is difficult and it is also not well documented how it is supposed to be adapted. It also turned out that the used version of the Linux machine and compiler programme influence whether or not the algorithm works or not. The error occurring on one system could not be resolved. This makes it not a very robust algorithm to use. In this research the algorithm was compiled using gcc version 4.4.7 on a CentOS Linux machine release version 6.4. For the sake of future reference a small documentation is written and added to this report in this appendix. The code and use of the actual model is better documented, for this refer to https://dhsvm.pnnl.gov/documentation.stm. This appendix is divided in a number of sections each describing the process of changing a different aspect of the algorithm. Each of these sections first name the documents that need to be changed and then what needs to be changed. The algorithm is placed in the folder "ensga2r". After changes in the code it is necessary to recompile the programs that are changed. If the problem definition is changed it is also necessary to recompile the ensga2r program, since the compiling of this uses the new lib-file created by the recompiling of the problem definition.

B.1 Adapting calibration period

This section will describe the procedures needed to change the calibration period that will be used.

B.1.1 Documents to be changed

1. /ensga2r/src/problemdef.c
2. /ensga2r/improved_dhsvm/configfiles
3. /ensga2r/improved_dhsvm/metfiles/
4. /ensga2r/improved_dhsvm/modelstate/
5. /ensga2r/improved_dhsvm/obsfile.txt

B.1.2 problemdef.c

In the problem definition file the amount of time steps for calibration are defined in line 11. If the calibration period is changed, and with that the amount of days, this number should be changed. The amount of time steps is equal to the total amount of time steps the model runs minus the spin up period of the model. As the algorithm is written now this is 61 timesteps, since the model is a daily model this corresponds to 61 days.

If the spin up period of the model is different the part where the *streamflow.only* file is loaded in the problem definition file should also be changed. Here the amount of lines to be deleted is defined through the amount of lines that state *fgets(string,200,fp);*. Each one of these lines defines a line that is to be deleted.

B.1.3 configfile

In the configfile the start and end date of the model run should be changed. These can be found in lines 76 and 77.

B.1.4 metfiles

The metfiles of the different stations need to be changed so the data they contain match with the given the start and end date that are set in the configfile.

B.1.5 modelstate

DHSVM requires four model state files that contain information on the channel, soil, interception and snow state on the first day of the model run. These model state files should match the given start date in the configfile.

B.1.6 obsfile.txt

The obsfile contains the observed discharges that are used for the calculation of the objectives. This file should contain the same number observations as the time steps given in the problem definition file. The first observation is on the day that the actual calibration begins, so the model run without the spin up time.

B.2 Adapting objectives

This section will describe the procedures needed to change the objectives that will be used for calibration.

B.2.1 Documents to be changed

1. /ensga2r/src/problemdef.c
2. /ensga2r/leaf/leaf.par

B.2.2 problemdef.c

The objectives are defined in the problem definition after the *streamflow.only* file is loaded. At this point the desired problem definition can be written using C as a language. At the bottom of the code, before the "box fitness assignment", the objectives should be assigned to the variable "obj[k]".

B.2.3 leaf.par

In the file leaf.par all the variables that influence the calibration are defined. The here defined amount of objectives should match the amount of objectives defined in the problem definition. Besides this, also for each objective an epsilon value needs to be given and an epsilon-performance value. The line where the epsilon-performance values are given starts with a 1 and after this the values for the different objectives are given.

When in this research a third objective was defined an extra empty line had to be included before the epsilon-performance values for the algorithm to be run. Why this was necessary is not known.

B.3 Adapting calibration parameters

This section will describe the procedures needed to change the calibration parameters that will be used.

B.3.1 Documents to be changed

1. /ensga2r/src/problemdef.c
2. /ensga2r/leaf/leaf.par
3. /ensga2r/improved_dhsvm/sourcecode/MainDHSVM.c
4. /ensga2r/improved_dhsvm/sourcecode/InitTables.c
5. /ensga2r/improved_dhsvm/sourcecode/InitConstants.c

B.3.2 problemdef.c

In the problem definition the model will be called to run. Depending on the number of calibration variables this command changes. Therefore the variable *name_for_system* needs to be changed. In the line below the name of the system for five calibration parameters is given. Here each *%f* is a float that gets assigned a value of a calibration parameter, stored in the variable *xreal*. When there are more calibration parameters, more *%f* should be added and for each of these also an extra *xreal[i]* should be included into the system's name. When there are less calibration parameters there should be less floats and *xreal[i]* given to the name of the system.

sprintf(name_for_system, "./improved_dhsvm/sourcecode/DHSVM3.1.1 ./improved_dhsvm/configfiles/jinhua200.txt %f %f %f %f %f %d %d %d %d", xreal[0], xreal[1], xreal[2], xreal[3], xreal[4], run, gen, popsize, mark);

B.3.3 leaf.par

In the leaf.par file the amount of calibration parameters and there ranges are defined. These should be adjusted such that the desired amount of calibration parameters is used. also the ranges should be set in such an order that they match the order that is set in the files InitTables.c and InitConstants.c.

B.3.4 MainDHSVM.c

In line 128 to 132 in this file the variable values and indicators of the model run are defined. In line 128 the parameter values for that model run are defined. This is done with the function *atof(argv[k])* for each calibration parameter. Here k indicates the parameter number and starts counting at 2.

In the lines 129 to 132 the indicators of which model run is performed at that moment. The same function is used for this as for the parameter values. The numbering of k continues where it has ended in the previous line.

B.3.5 InitTables.c and InitConstants.c

In these files the parameters that are to be used for calibration are indicated. The file InitConstants.c contains the parameters that are constant over space, such as LAI rain multiplier in this research. InitTables.c contains the parameters that vary over space and thus related to the soil and vegetation. The variable *CaliPara* contains the values of the parameters assigned by the algorithm.

The parameters that should be used to calibrated can be added through calling the value in this variable. The order of the parameter values in this variable corresponds to the order of ranges set in the leaf.par file. If the parameter only, such as the lateral conductivity in this research, has one value for each soil layer and month the parameter value can be called like the line below.

*(*SType)[i].KsLat = CaliPara[k];*

This line should be placed **below** the line where the variable is introduced in the file. This looks as follows for the lateral conductivity.

*if (!CopyFloat(&((*SType)[i].KsLat), VarStr[lateral_ks], 1)) ReportError(KeyName[lateral_ks], 51);*

The correct parameter values should be calculated if a parameter has more than one value for each soil layer and month. This is done through the line below for the porosity. If more values are needed, for example by the overstory monthly LAI, more %lf should be added for storing the values.

*sprintf(VarStr[porosity],"%lf %lf %lf",CaliPara[i],0.93*CaliPara[i],0.9*CaliPara[i]);*

This is placed directly **above** the line where the variable is introduced in the file.

C Calibration values

The calibration of the model ins an iterative process in which the ranges of the parameter values are changed after each optimisation run. This is because if the range of the parameter is too large it might not find the optimum solution within the maximum amount of function evaluations. However, if the parameter range is too small the optimum solution might not be found, because it lies outside the given ranges. In this appendix the ranges for the parameters at each iteration are given in Table 10, as well as the optimum Nash-Sutcliffe coefficient, PBIAS-value and Mean Fourth-power Error.

Table 10: Ranges parameters for optimisation iterations

	Iteration	Rj [-]	K [m/s]	ϕ [-]	θ_{fc} [m^3/m^3]	θ_{wp} [m^3/m^3]	NS	PBIAS	M4E
21 stations	I	1E-5~1E-3	1E-5~0.09	0.4~0.6	0.23~0.4	0.05~0.23	0.80	0.17	5.49E+8
	II	1E-5~5E-4	1E-3~0.09	0.4~0.5	0.23~0.3	0.1~0.2	0.80	0.020	5.45E+8
	III	2E-4~4E-4	0.01~0.02	0.4~0.45	0.24~0.26	0.12~0.17	0.80	0.023	5.45E+8
	IV	2.5E-4~3.5E-4	0.01~0.015	0.42~0.45	0.25~0.26	0.16~0.17	0.80	0.024	5.44E+8
	V	2.7E-4~3E-4	0.01~0.013	0.425~0.445	0.25~0.255	0.16~0.165	0.80	0.024	5.44E+8
5 stations	I	1E-5~1E-3	1E-5~0.09	0.4~0.6	0.23~0.4	0.05~0.23	0.80	0.10	6.01E+8
	II	2E-4~8E-4	5E-3~0.03	0.5~0.6	0.3~0.4	0.05~0.08	0.80	0.12	5.75E+8
	III	4E-4~8E-4	8E-3~0.02	0.55~0.6	0.35~0.4	0.05~0.06	0.80	0.12	5.73E+8
	IV	4E-4~7E-4	0.01~0.02	0.56~0.6	0.35~0.39	0.051~0.059	0.80	0.10	5.93E+8
	V	5E-4~7E-4	0.01~0.015	0.58~0.6	0.35~0.36	0.051~0.052	0.80	0.075	5.88E+8
	VI	5E-4~6E-4	0.01~0.012	0.58~0.59	0.35~0.355	0.051~0.0515	0.80	0.075	5.87E+8