中山大學
SUN YAT-SEN UNIVERSITY

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Urbanization and its impact on flood response

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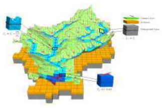
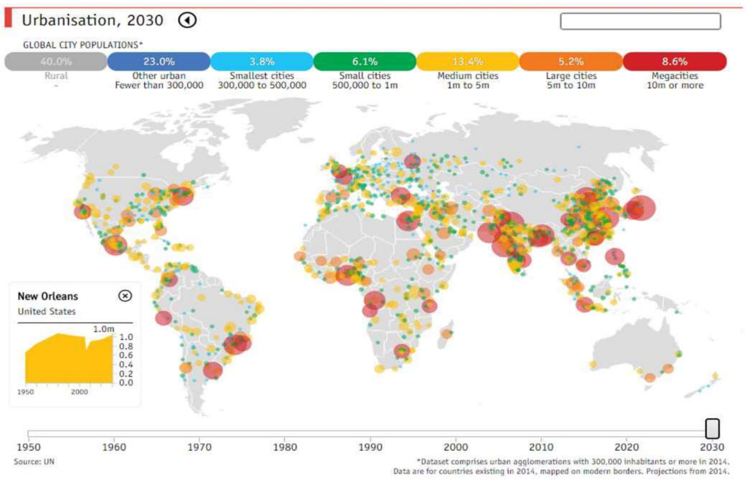


Contents

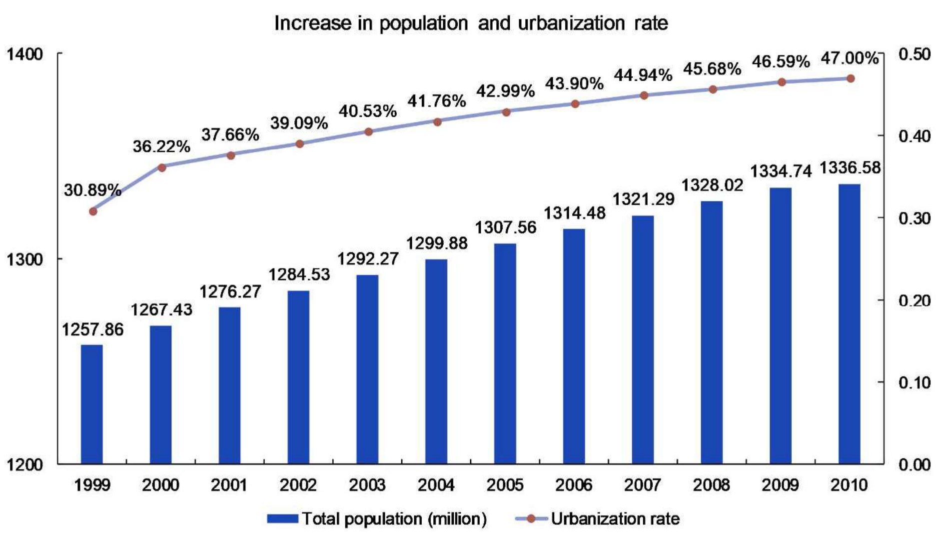
INTRODUCTION

- ➢ Urbanization is a worldwide trend
  - ✓ In 2009, 50% world population lived in the urbanized area, to 2030, 65%...(UN, 2010)



INTRODUCTION

- ➢ China had a rapid urbanization
  - ✓ In 1980: 17% urban population, 2011: 50%, to 2050, 65%...(Fang et al., Wang, 2011)

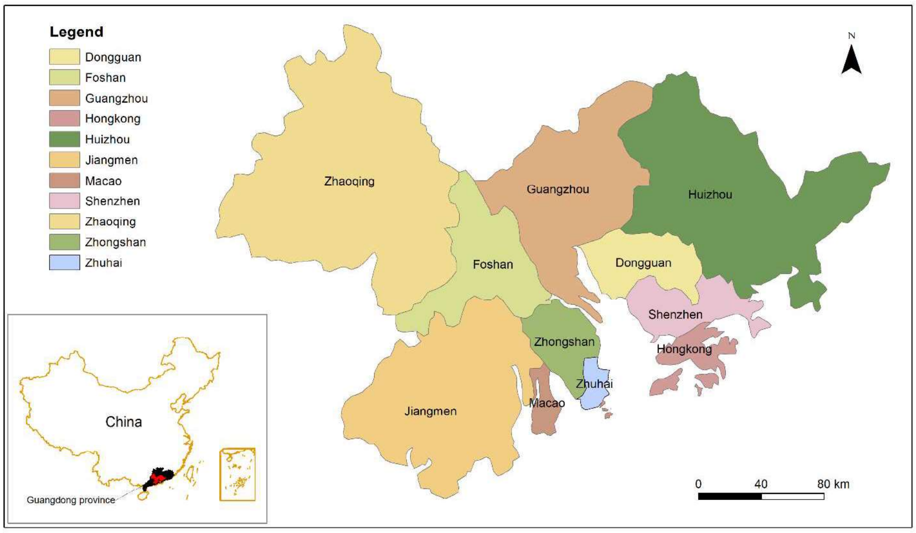


INTRODUCTION

- ➢ Urbanization causes many changes
  - ✓ land use/cover(LUC) change, i.e., increasing impervious surfaces
- ➢ Thus having significant impact on hydrological responses
  - ✓ Increasing flood peak flow
  - ✓ Enlarging flood runoff coefficient
  - ✓ More flooding

INTRODUCTION

- ➢ The Guangdong-Hong Kong-Macao Greater Bay Area(GHM Bay Area)
  - ✓ China’s national development zone
  - ✓ 11 megacities: Guangzhou, Shenzhen, Hong Kong, Macao
  - ✓ Population: 69.57M, GDP: USD1600B (2017)
  - ✓ Area: 560,000 km^2, Highly urbanized



Source: https://www.bayarea.gov.hk/en/home/index.html

INTRODUCTION

- Urbanization causes more flooding.
- This is particularly true in the GHM Bay Area

INTRODUCTION

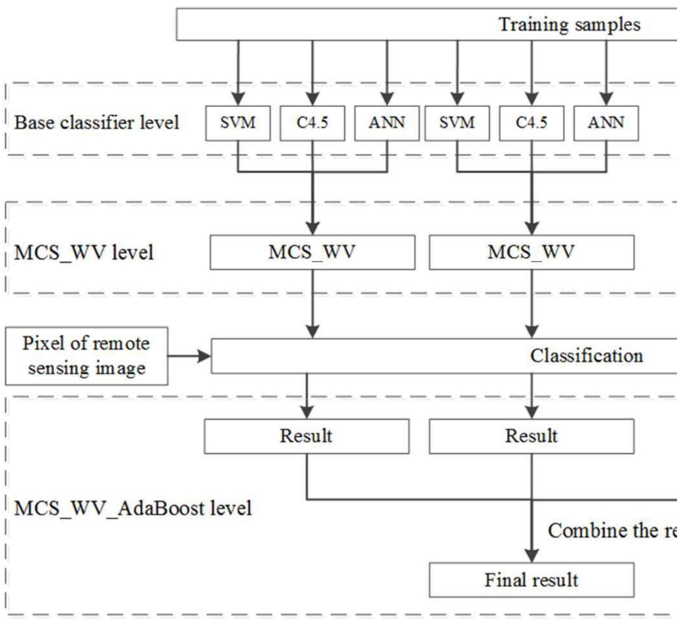
- Quantifying the impact of urbanization on flood responses in this area is very important
- Challenges
  - ✓ Lacking series LUC change data
  - ✓ Lacking appropriate hydrological model and hydrological data for calibrating model parameters
- Purposes of this study
  - ✓ To develop appropriate techniques for quantifying the impact of urbanization on flood responses in the area

INTRODUCTION

- Works done
  - ✓ Proposed algorithm for quantify LUC changes for the past 3 decades by employing satellite remote sensing images
  - ✓ Developed hydrological model for flood simulation, and determine model parameters associated with LUC change
  - ✓ Simulated flood processes with parameters associated with LUC change
  - ✓ Analyze impact of urbanization on flood responses, i.e., peak flow and runoff coefficient

LUC change

- Multiple classifiers syst



remote sensing

MDPI

Article

Improving Land Use/Cover Classification with a Multiple Classifier System Using AdaBoost Integration Technique

Yangbo Chen [1,*], Peng Dou [1] and Xiaojun Yang [2]

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Abstract: Guangzhou has experienced a rapid urbanization since 1978 when China initiated the economic reform, resulting in significant land use/cover changes (LUC). To produce a time series of accurate LUC dataset that can be used to study urbanization and its impacts, Landsat imagery was used to map LUC changes in Guangzhou from 1987 to 2015 at a three-year interval using a multiple classifier system (MCS). The system was based on a weighted vector to combine base classifiers of different classification algorithms, and was improved using the AdaBoost technique. The new classification method used support vector machines (SVM), C4.5 decision tree, and neural networks (ANN) as the training algorithms of the base classifiers, and produced higher overall classification accuracy (88.12%) and Kappa coefficient (0.87) than each base classifier did. The results of the experiment showed that, based on the accuracy improvement of each class, the overall accuracy was improved effectively, which combined advantages from each base classifier. The new method is of high robustness and low risk of overfitting, and is reliable and accurate, and could be used for analyzing urbanization processes and its impacts.

Keywords: multiple classifiers system (MCS); AdaBoost; remote sensing; classification algorithms

1. Introduction

Land use/cover (LUC) has been changed drastically due to urbanization in the past decades [1,2], and more built area has appeared to provide space for development. Such changes also caused a series of negative effects on human society, such as increasing flood risk [3], deteriorating environment [4], degrading ecosystem [5], and so on. To better understand these impacts, LUC changes (LUCC) caused by urbanization need to be quantified accurately. Remote sensing is the latest technique that has been used to estimate LUCC [6–9], and the Landsat imagery acquired by MSS, TM, ETM+ and OLI sensors have been widely used for such a purpose [10] due to its long records and free availability [11,12].

Quantitative LUCC estimation has mainly been driven from remotely sensed imagery using various classification algorithms [13,14], which can be divided into supervised algorithms and unsupervised algorithm [15]. Decision trees, support vector machines (SVM), artificial neural networks (ANN) and maximum likelihood classifier are supervised classification algorithms [16–18], and K-means algorithm, fuzzy c-means algorithm and AP cluster algorithm are typical unsupervised classification algorithms [19–22]. These algorithms have been widely used in estimating LUCC with satellite remote sensing. For example, Pal and Mather [23] used SVM to classify land cover with Landsat ETM+ images, and Tong et al. [24] detected urban land changes of Shanghai in 1990, 2000 and 2006 by using artificial backpropagation neural network (BPN) with Landsat TM images.

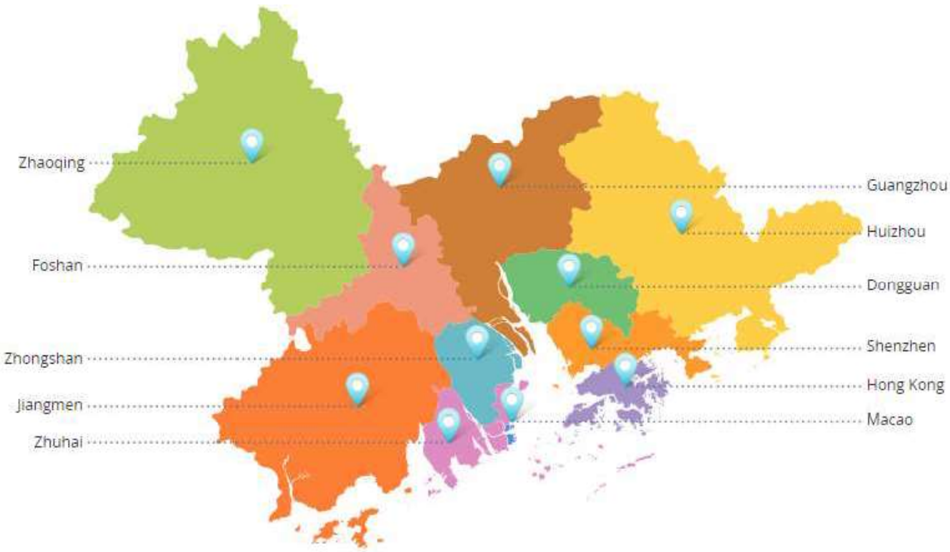
Remote Sens. **2017**, *9*, 1055; doi:10.3390/rs9101055 www.mdpi.com/journal/remotesensing

LUC changes estimation

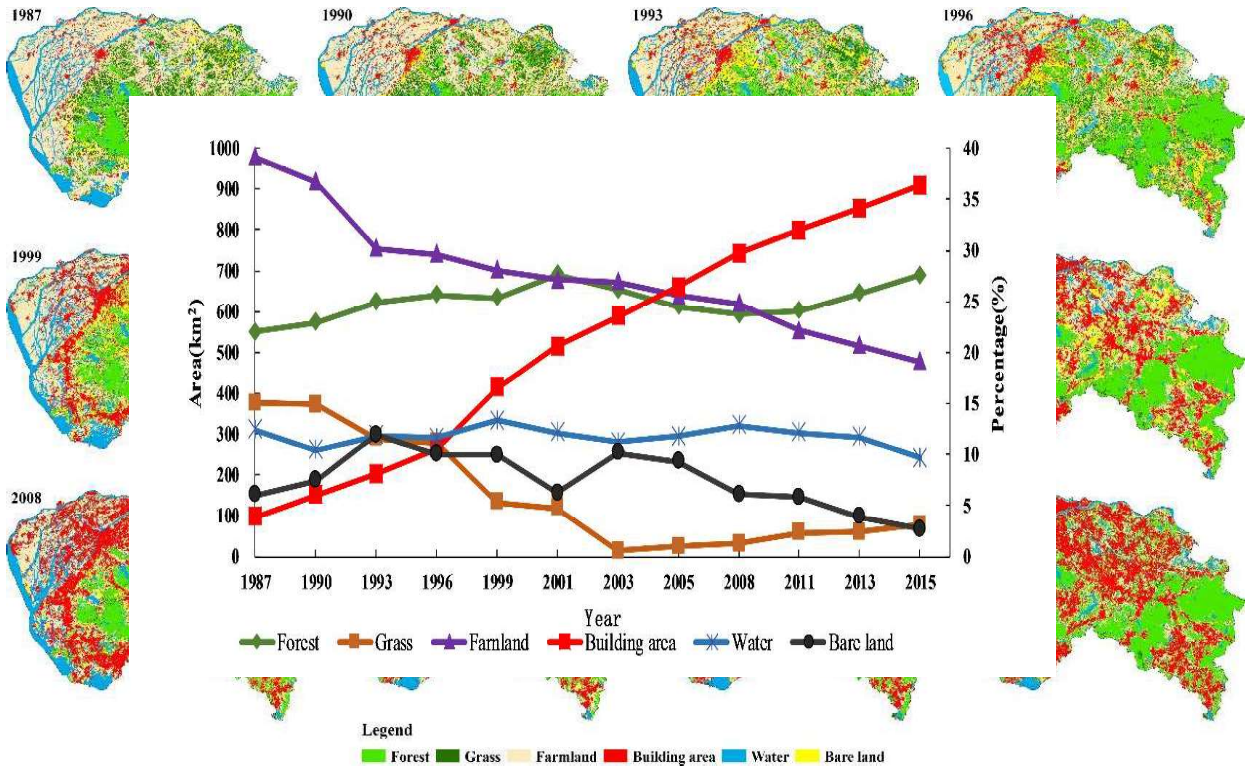
- LUC change from 1987 to 2015 has been estimated with Landsat remote sensing images at a roughly 3-year interval. 6 types LUC used.
  - ✓ Built-up(urbanized) area
  - ✓ Farm land
  - ✓ Forest land
  - ✓ Grass land
  - ✓ Bare land
  - ✓ Water body

LUC changes estimation

- Multiple classifier system algorithm is employed for the LUC estimation(Chen et al., 2017)
- Dataset for 6 cities established
  - ✓ Guangzhou
  - ✓ Dongguan
  - ✓ Shenzhen
  - ✓ Foshan
  - ✓ Zhongshan
  - ✓ Zhuhai



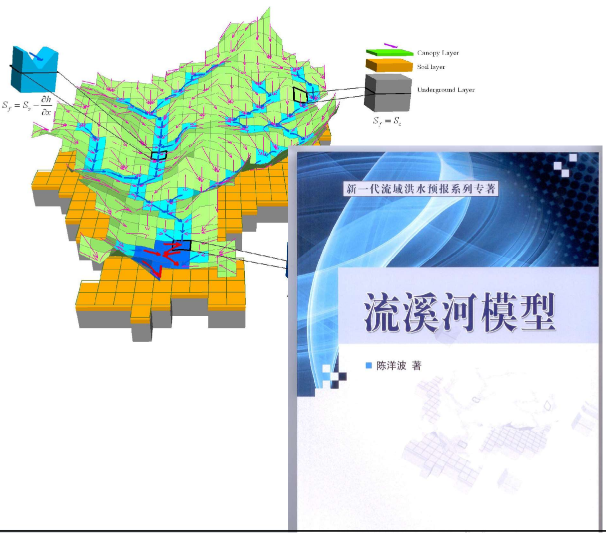
Urbanization: Dongguan



Hydrological model and parameter

- **Liuxihe model**

  A physically based distributed hydrological model has been proposed for catchment flood processes simulation and prediction.




Liuxihe Model and Its Modeling to River Basin Flood

Yangbo Chen[1], Qiwei Ren[2], Fenghua Huang[3], Huijun Xu[4], and Ian Cluckie[5]


Hydrol. Earth Syst. Sci., 20, 375–392, 2016
www.hydrol-earth-syst-sci.net/20/375/2016/
doi:10.5194/hess-20-375-2016

Hydrology and Earth System Sciences

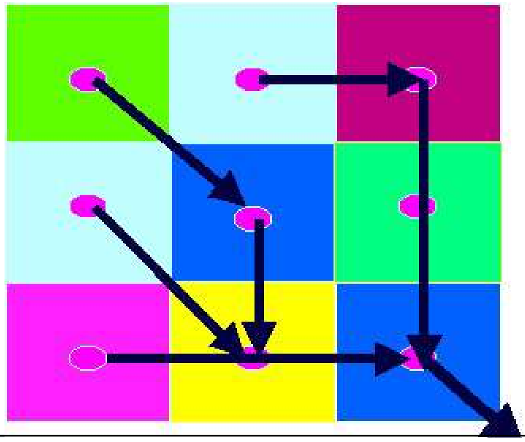
Improving flood forecasting capability of physically based distributed hydrological models by parameter optimization

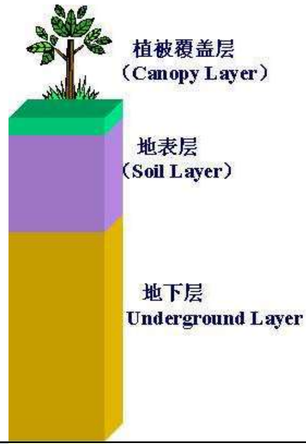
Y. Chen[1], J. Li[1], and H. Xu[2]

Published by Copernicus Publications on behalf of the European Geosciences Union.

Liuxihe Model

- Horizontally divided into grid cells that is further classified as hillslop cell, river cell and reservoir cell
- Vertically divided into layers
- Runoff produced on cell
- Runoff routes over cells and inter-cells





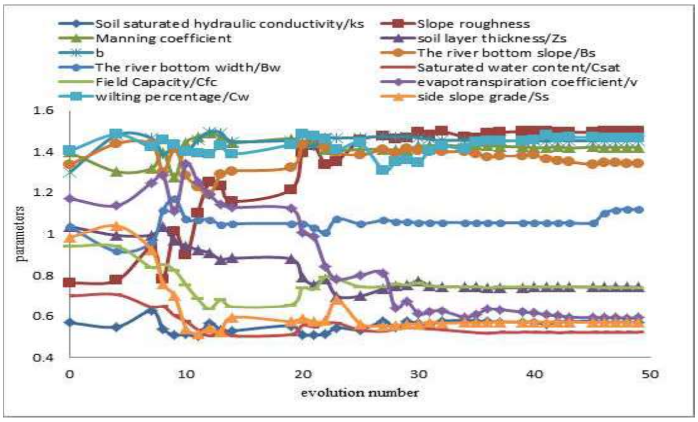
Model parameter determination

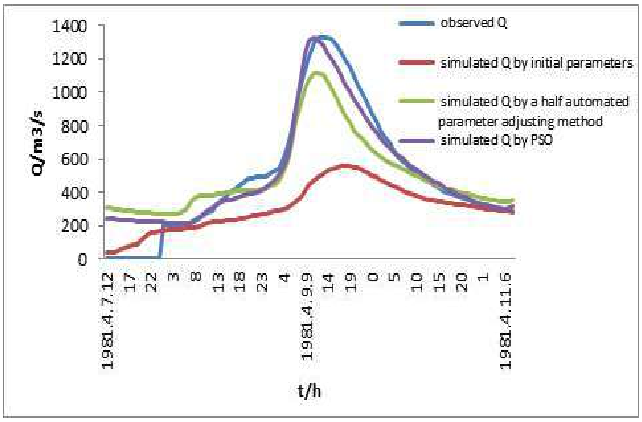
Physically deriving parameters from cell properties

type	Parameter
meteorological	potential evaporation rate
topographical	flow direction, slope
Soil related	soil thickness, water content at saturation condition, water content at field condition, water content at wilting point, hydraulic conductivity at saturation, groundwater recession coefficient
land use related	Roughness, evaporation capacity

Parameter optimization

- Automatic optimization
  - ✓The Particle Swarm Optimizaton method (Eberhart and Kennedy, 1995) is employed to do this job
  - ✓PSO was tested in three catchment





Software tools

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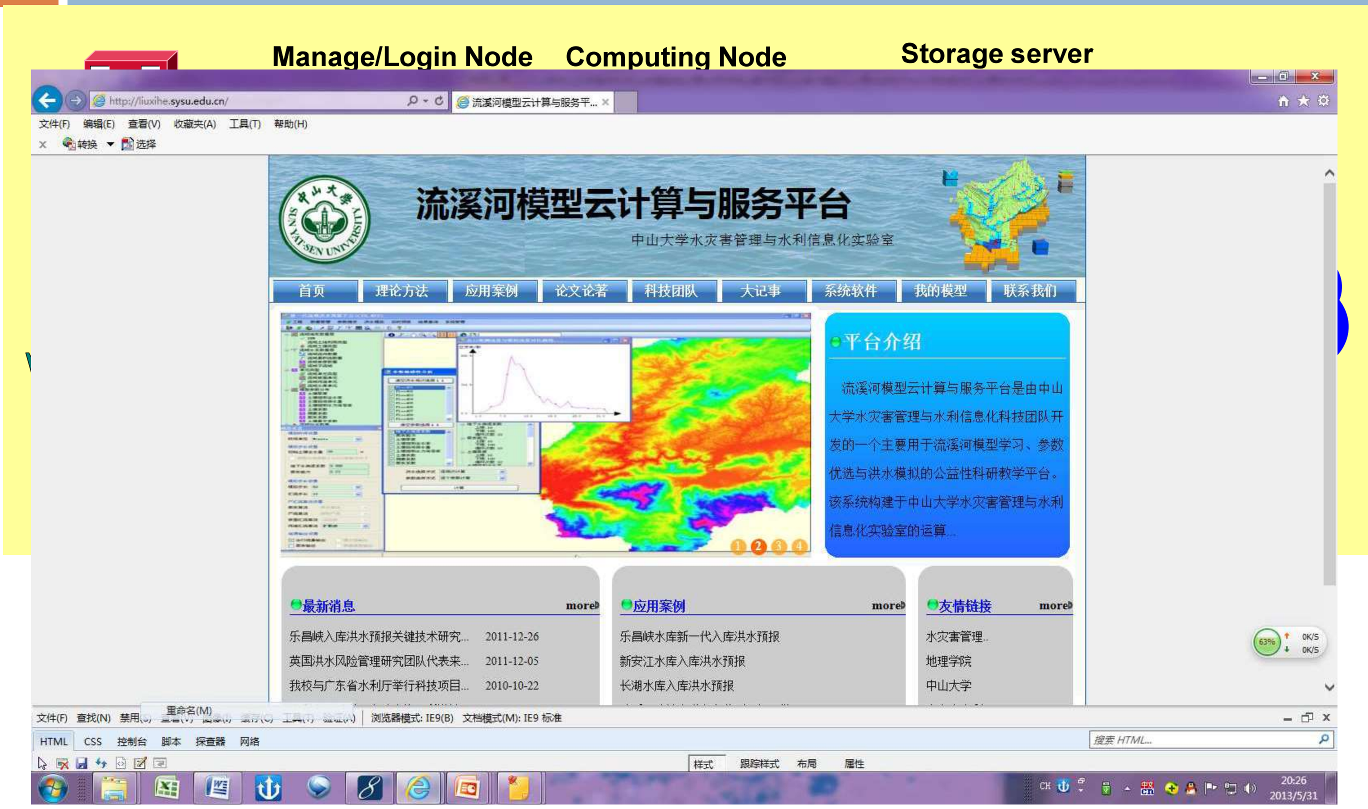
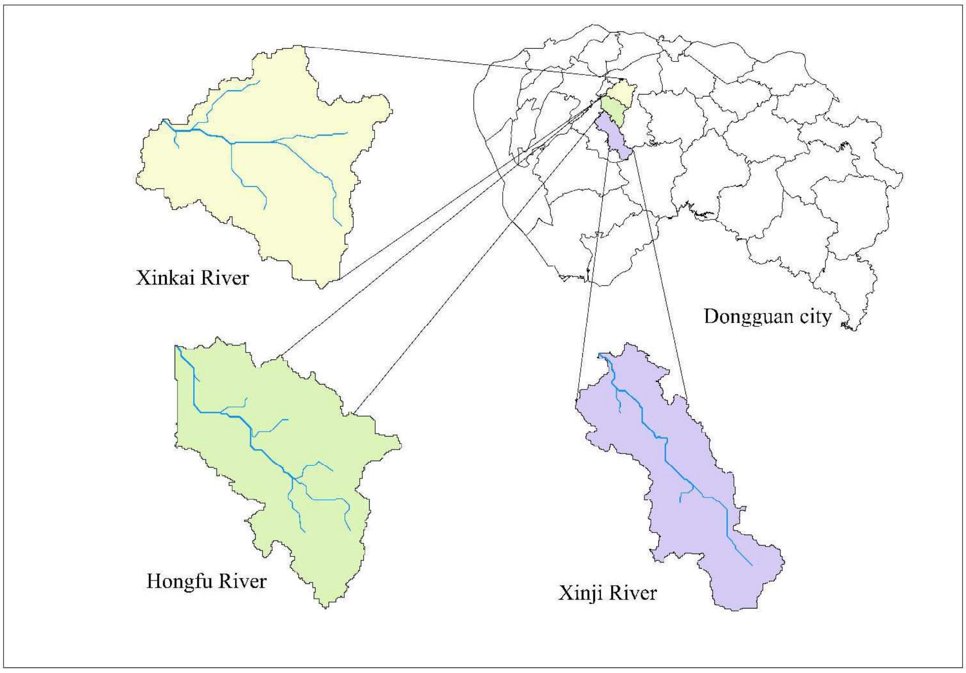
- Standardized software system
  - ✓ Liuxihe Model System: model set up
  - ✓ Liuxihe Model Cloud: parameter optimization
  - ✓ Liuxihe Model System Real-time Flood Forecasting System

Liuxihe Model Cloud



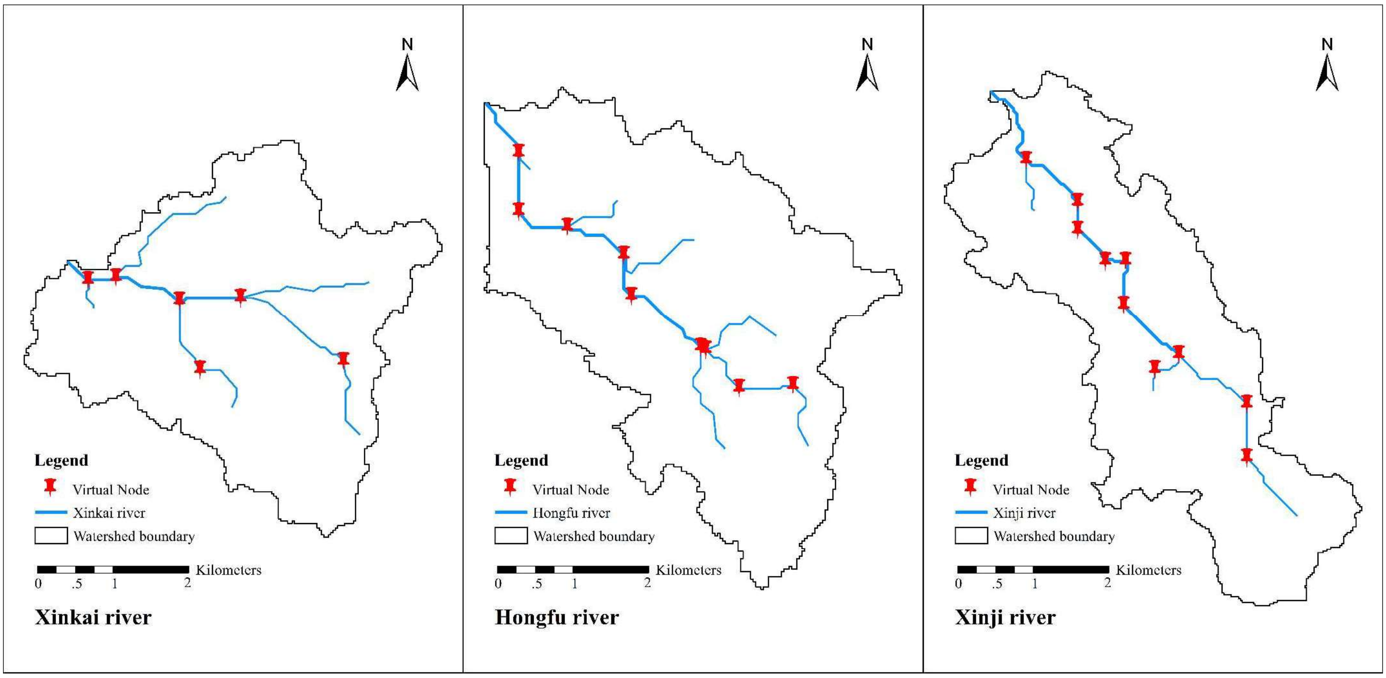
Hydrological model and parameter

Watersheds studied



Hydrological model and parameter

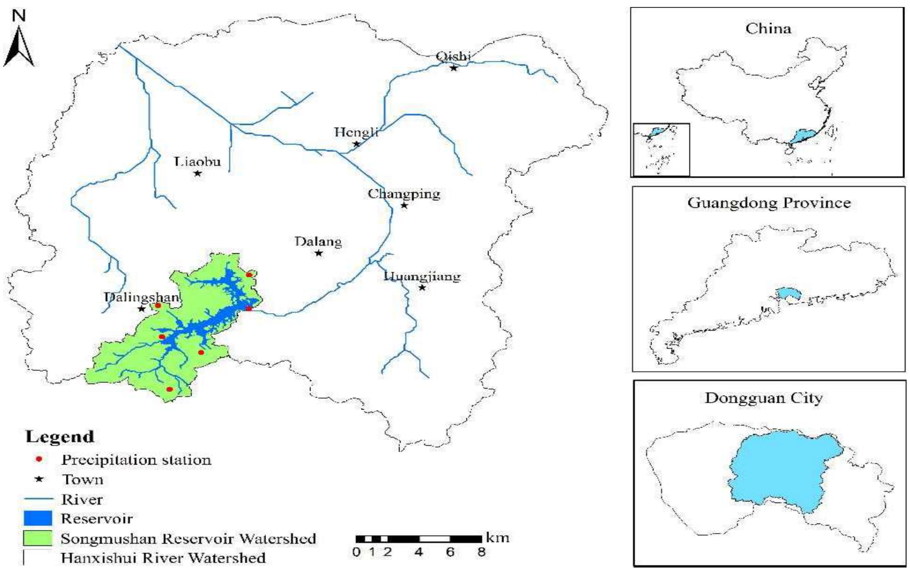
Model structure



Hydrological model and parameter

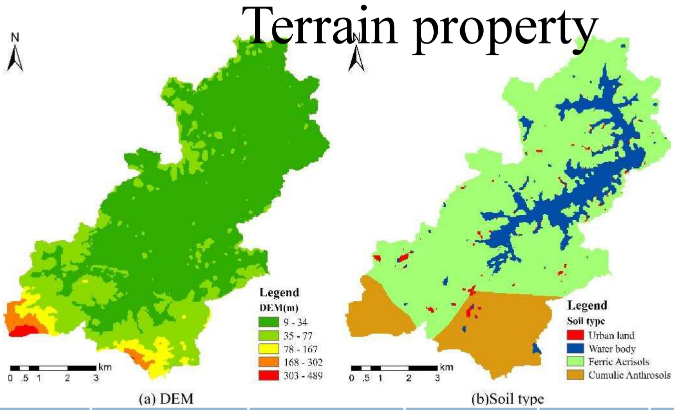
- **parameter optimization and regionalization**

Songmushan watershed in Dongguan City: with full hydrological observation in recent years, used for model parameter optimization and validation.

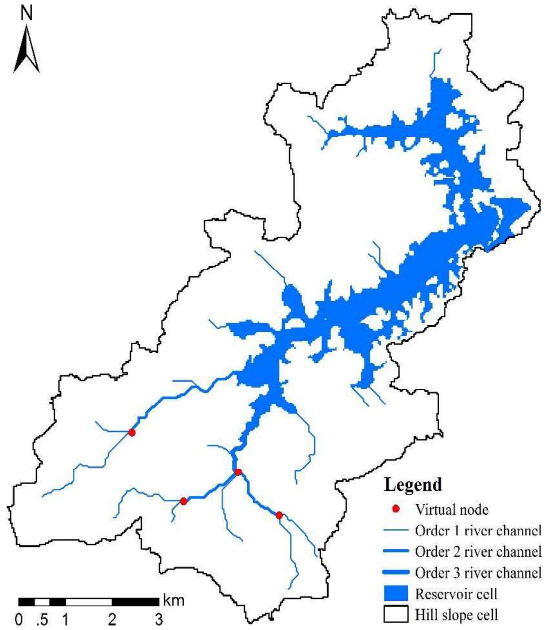


Parameter optimization and regionalization：Songmushan Watershed

Terrain property



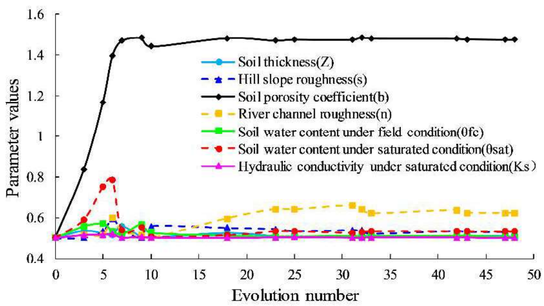
Model structure



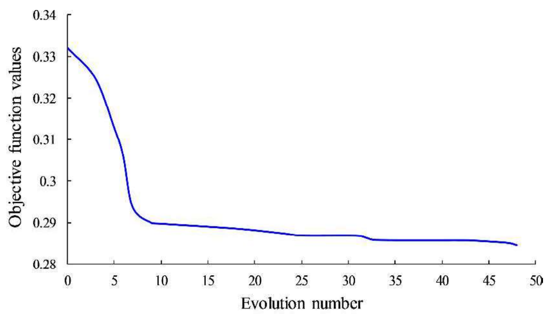
Flood event no.	Start time (yyyymmddhh)	End time (yyyymmddhh)	Total rainfall (mm)	Peak flow (m^3/s)	Flood scale
20080419	2008041910	2008042018	110.6	111.1	light
20080612	2008061219	2008061412	271.0	328.6	heavy
20080625	2008062500	2008062623	360.3	445.8	heavy
20090523	2009052304	2009052401	104.4	133.3	light
20090609	2009060900	2009060916	127.7	158.3	medium
20110516	2011051608	2011051702	60.1	102.8	light
20110808	2011080811	2011080900	48.6	136.1	light
20130815	2013081517	2013081823	351.3	254.7	heavy
20140511	2014051103	2014051122	110.7	208.3	medium
20140819	2014081914	2014082018	98.0	158.3	medium
20150520	2015052009	2015052103	90.1	141.7	light
20150523	2015052305	2015052404	100.9	194.4	medium
20150720	2015072022	2015072119	171.8	208.3	medium

Parameter optimization and regionalization：Songmushan Watershed

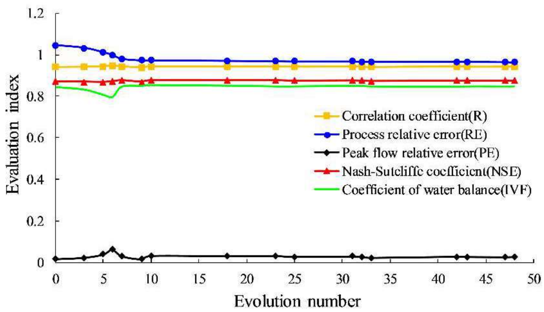
Parameter optimization: flood event: 20080625



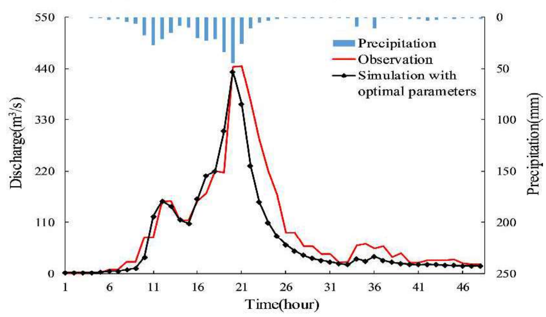
(a) The evolution of parameters



(b)The evolution of objective function



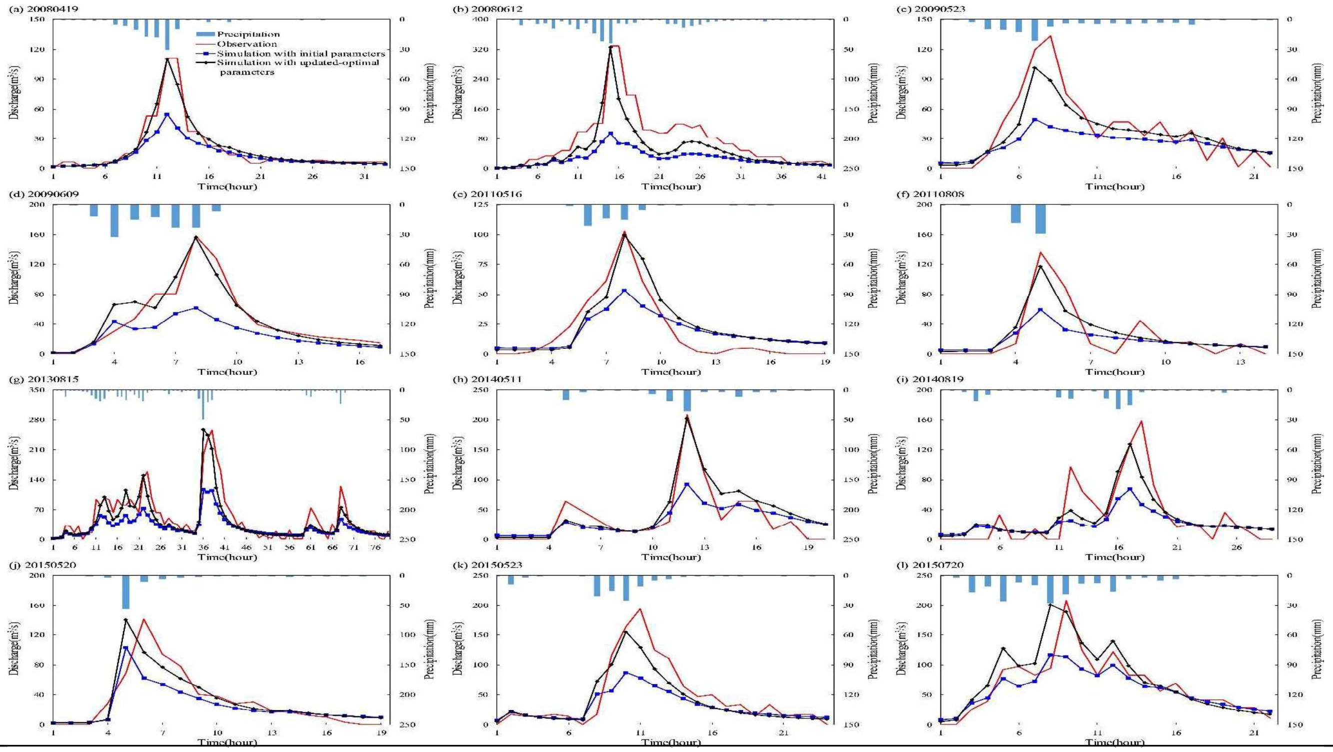
(c)The evolution of statistical indicators



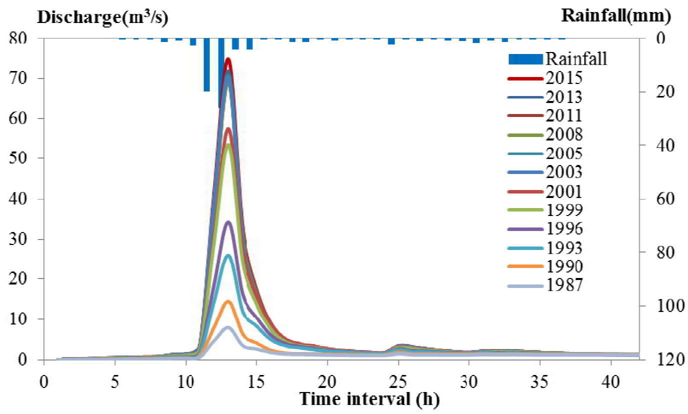
(d)Simulation(20080625)

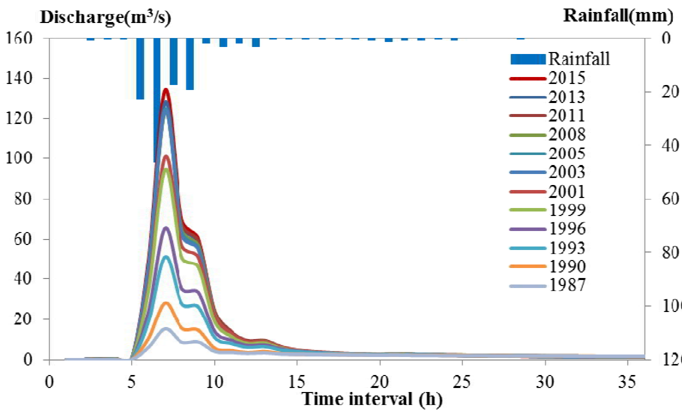
Parameter optimization and regionalization：Songmushan Watershed

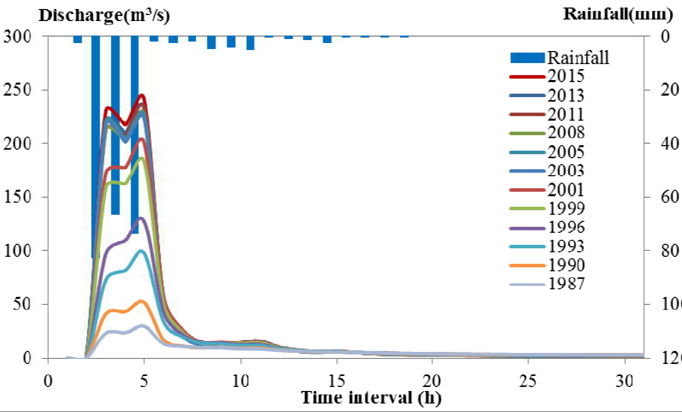
Model validation: **parameter optimization is crucial**



Flood simulation: Xinkai River

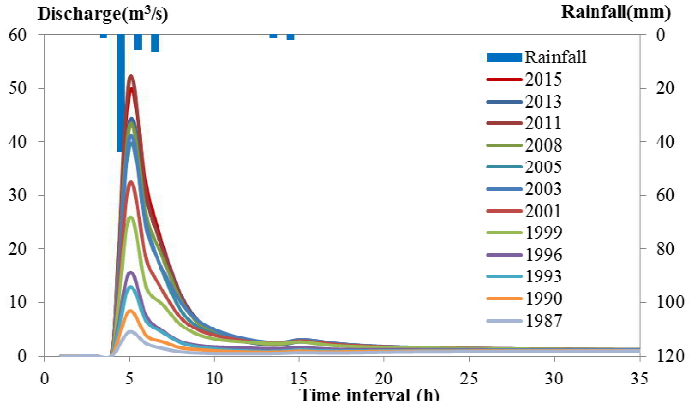


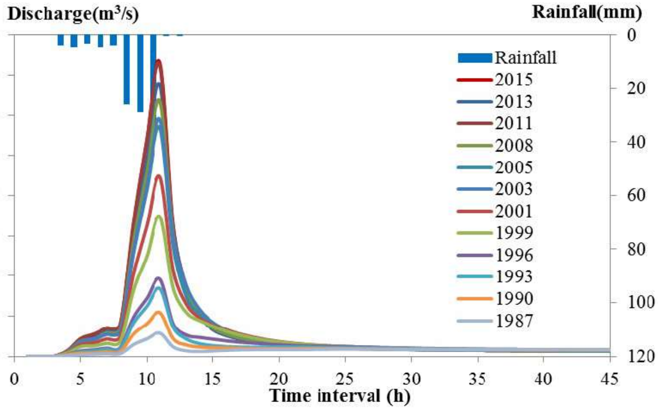


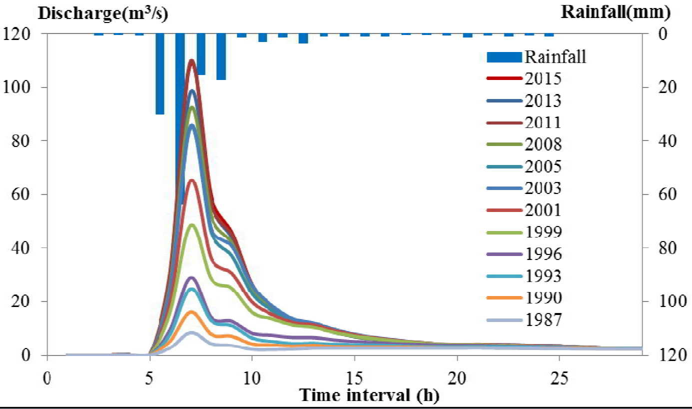


Precipitation of three storms were collected and drive the model, one heavy, one medium and one light

Flood simulation: Hongfu River

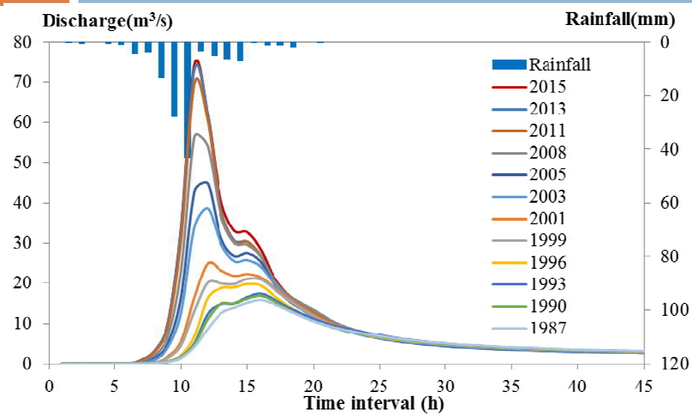


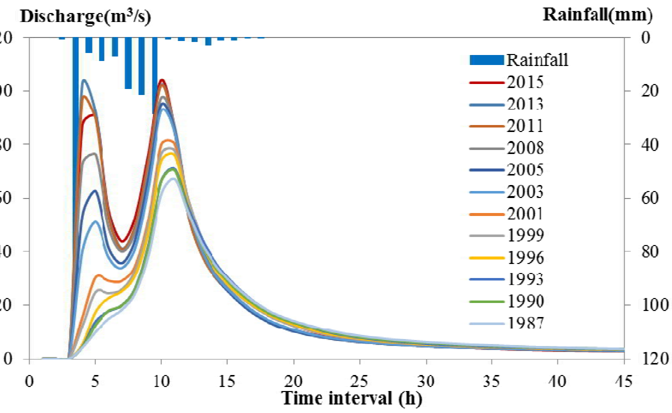


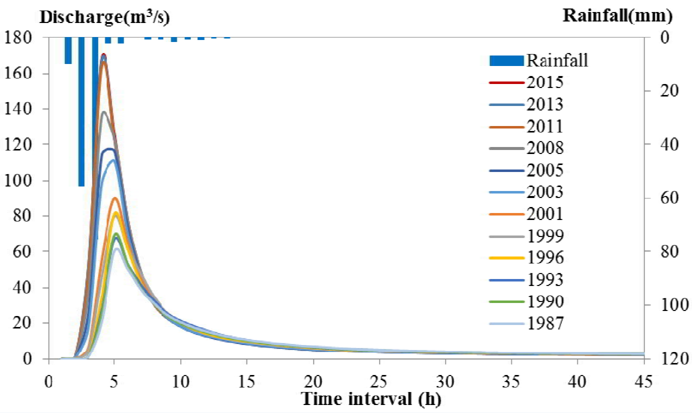


Precipitation of three storms were collected and drive the model, one heavy, one medium and one light

Flood simulation: Xinji River





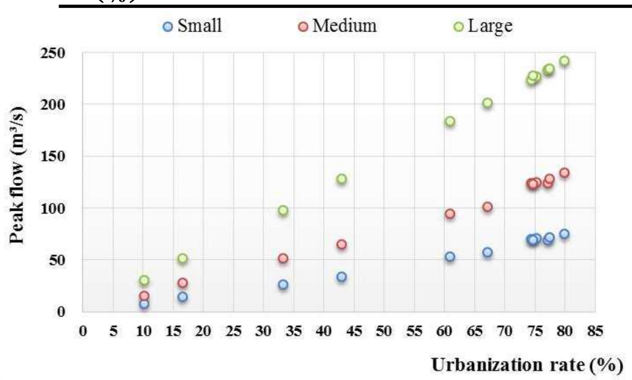


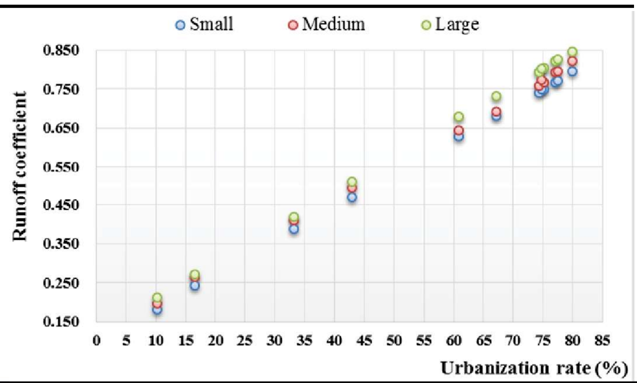
Precipitation of three storms were collected and drive the model, one heavy, one medium and one light

Impact of LUCC on flood responses

Xinkai River

Storms		Small		Medium		Large	
Years	Urbanization rate（%）	Peak flow（m^3/s）	Runoff coefficient	Peak flow（m^3/s）	Runoff coefficient	Peak flow（m^3/s）	Runoff coefficient
1987	10.2	7.89	0.180	15.28	0.196	30.15	0.211
1990	16.5	14.46	0.243	28.19	0.265	51.82	0.271
1993	33.2	25.90	0.387	51.24	0.411	97.86	0.419
1996	42.9	34.17	0.469	65.37	0.493	127.97	0.509
1999	60.9	53.43	0.628	94.55	0.643	183.54	0.678
2001	67.1	57.47	0.680	100.84	0.693	201.30	0.732
2003	74.4	69.83	0.740	123.78	0.758	223.77	0.794
2005	75.2	70.51	0.750	124.60	0.766	226.73	0.804
2008	74.7	69.04	0.750	123.27	0.773	227.32	0.802
2011	77.1	69.37	0.767	124.09	0.793	233.48	0.822
2013	77.5	71.70	0.772	127.96	0.795	233.98	0.826
2015	79.9	74.72	0.796	134.41	0.822	241.69	0.846
increase（%）	683	847	342	780	319	702	301

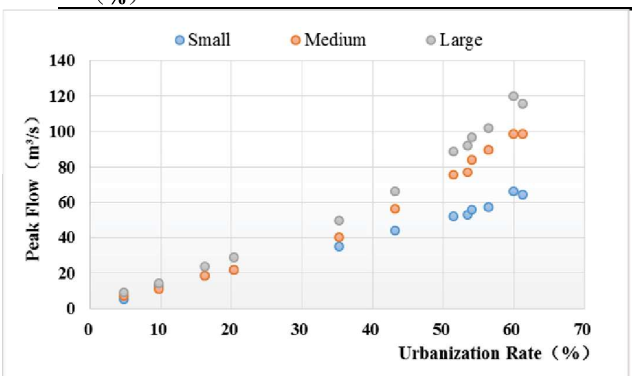


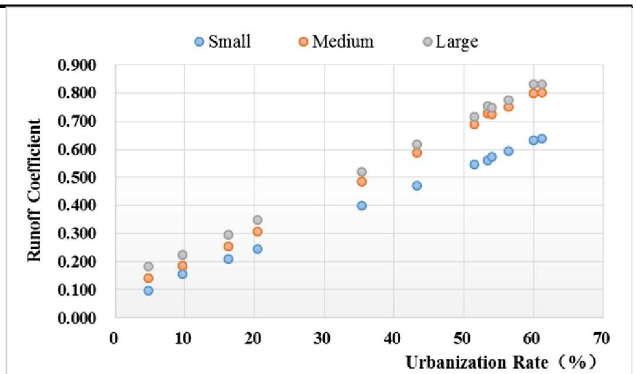


Impact of LUCC on flood responses

Hongfu River

Storms		Small		Medium		Large	
Years	Urbanization rate（%）	Peak flow（m^3/s）	Runoff coefficient	Peak flow（m^3/s）	Runoff coefficient	Peak flow（m^3/s）	Runoff coefficient
1987	4.8	5.50	0.096	7.17	0.141	9.22	0.181
1990	9.7	13.00	0.156	11.20	0.186	14.48	0.224
1993	16.2	18.70	0.208	18.58	0.253	23.59	0.294
1996	20.4	21.80	0.246	22.01	0.307	29.13	0.348
1999	35.3	35.10	0.398	40.11	0.486	49.49	0.521
2001	43.2	44.00	0.470	56.33	0.589	66.03	0.617
2003	53.4	53.20	0.562	77.21	0.726	92.20	0.753
2005	51.5	52.10	0.546	75.40	0.688	88.83	0.716
2008	54.0	56.00	0.572	84.23	0.724	96.59	0.748
2011	60.0	66.00	0.633	98.54	0.800	119.82	0.830
2013	56.4	57.10	0.593	89.66	0.752	101.88	0.776
2015	61.2	64.30	0.639	98.78	0.802	115.78	0.831
increase（%）	1175	1069	566	1277	469	1156	359

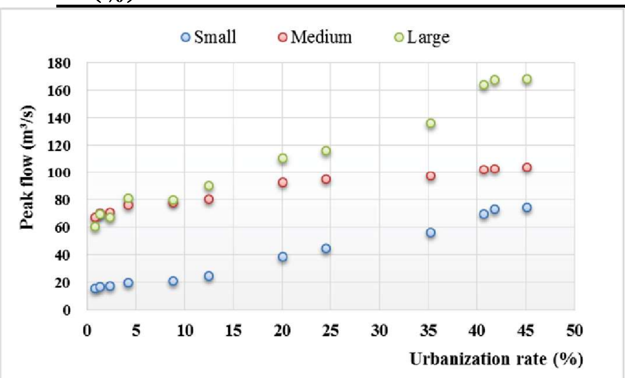


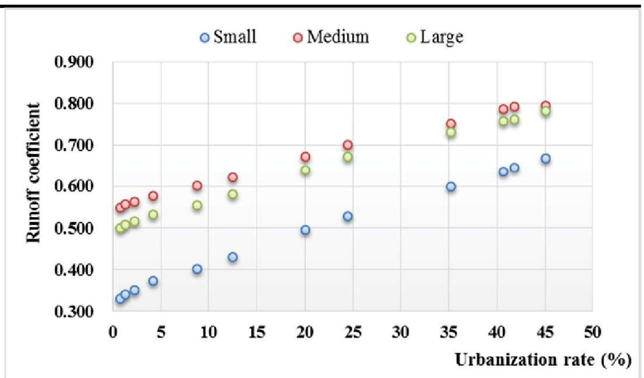


Impact of LUCC on flood responses

Xinji River

Storms		Small		Medium		Large	
Years	Urbanization rate (%)	Peak flow (m^3/s)	Runoff coefficient	Peak flow (m^3/s)	Runoff coefficient	Peak flow (m^3/s)	Runoff coefficient
1987	0.8	15.82	0.330	67.09	0.549	60.44	0.499
1990	1.3	16.89	0.340	70.37	0.556	69.57	0.507
1993	2.3	17.48	0.350	70.86	0.562	67.26	0.515
1996	4.2	19.81	0.372	76.15	0.577	81.32	0.532
1999	8.8	21.12	0.401	77.89	0.600	80.18	0.554
2001	12.5	24.91	0.429	80.26	0.621	90.09	0.580
2003	20.1	38.68	0.495	92.67	0.672	110.89	0.640
2005	24.5	44.83	0.527	94.96	0.701	116.51	0.672
2008	35.2	56.45	0.599	97.43	0.752	136.37	0.732
2011	40.7	69.63	0.636	102.08	0.786	164.07	0.757
2013	41.8	73.11	0.645	102.64	0.792	167.65	0.762
2015	45.1	74.34	0.668	104.09	0.794	168.42	0.782
increase (%)	5537	370	102	55	45	179	57





Conclusions

- ✓ LUC changes of 6 cities in the Guangdong-Hong Kong-Macao Greater Bay Area has been estimated by using Landsat satellite imageries, and very rapid urbanization pattern has been found
- ✓ Models in 3 watersheds has been set up by a regionalized parameters optimized in a watershed, and flood processes has been simulated that is associated with changing LUC
- ✓ Impact of urbanization on watershed flood responses has been quantified in 3 watersheds, with biggest peak flow increasing of more than 10 times, and runoff coefficient increasing of more then 3 times, makes it the biggest impact worldwide

Future works

- ✓ More watersheds will be studied in the Guangdong-Hong Kong-Macao Greater Bay area
- ✓ Joint impact of urbanization and climate change on flood responses will be studied also
- ✓ International cooperation is sought to have case studies in watersheds of other Asian countries where significant urbanization has occurred or will occur

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Thanks！

Questions?