

See discussions, stats, and author profiles for this publication at: <https://www.researchgate.net/publication/324712457>

# Large-Scale Flood-Inundation Modeling in the Mekong River Basin

Article in *Journal of Hydrologic Engineering* · April 2018

DOI: 10.1061/(ASCE)HE.1943-5584.0001664

CITATION

1

READS

625

5 authors, including:



**Try Sophal**

Kyoto University

6 PUBLICATIONS 3 CITATIONS

[SEE PROFILE](#)



**Giha Lee**

Kyungpook National University

139 PUBLICATIONS 171 CITATIONS

[SEE PROFILE](#)



**Wansik Yu**

Chungnam National University

28 PUBLICATIONS 82 CITATIONS

[SEE PROFILE](#)



**Chantha Oeurng**

Institute of Technology of Cambodia

49 PUBLICATIONS 360 CITATIONS

[SEE PROFILE](#)

Some of the authors of this publication are also working on these related projects:



Improved surface-groundwater irrigation for crop diversification in Tonle Sap Lake Basin: Case study in Chreybak Catchment [View project](#)



Asian Pacific FRIEND-WATER [View project](#)

# Large-Scale Flood-Inundation Modeling in the Mekong River Basin

Sophal Try<sup>1</sup>; Giha Lee<sup>2</sup>; Wansik Yu<sup>3</sup>; Chantha Oeurng<sup>4</sup>; and Changlae Jang<sup>5</sup>

**Abstract:** Flood impacts threaten the socioeconomic conditions of peoples' lives in the Mekong River Basin. In this study, the rainfall-runoff-inundation (RRI) model, capable of simulating rainfall runoff and flood inundation simultaneously, was used to enhance understanding of flooding characteristics in this region by using grid-satellite-based rainfall. Input data for the simulation included HydroSHEDS topographic data, APHRODITE precipitation data, MODIS land use data, and river cross sections. Moreover, the shuffled complex evolution developed at The University of Arizona (SCE-UA) global optimization method was integrated with the RRI model to calibrate sensitive parameters. In this study, the flood event in 2000 has been selected in the Mekong River Basin. The simulation results were compared with observed discharges at monitoring stations along the river and an inundation map from Landsat 7 satellite imagery and the Mekong River Commission (MRC) data. The results indicated good agreement between the observed and simulated discharges, for example, with Nash-Sutcliffe efficiency (NSE) = 0.86 at the Stung Treng Station. The model predicted inundation extent with a success rate (SR) = 67.50% and modified success rate (MSR) = 74.53% compared with satellite Landsat 7, and SR = 68.27% and MSR = 75.11% compared with MRC data. Therefore, the RRI model was successfully used to simulate a large-scale inundation flood event in 2000 using a grid precipitation data set in the Mekong River Basin. However, the underestimation might be due to the uncertainties of input data, river geometry, the large scale of the basin, coarse resolution of topographic data, and error in remote sensing image in detecting the flood extent. DOI: 10.1061/(ASCE)HE.1943-5584.0001664. © 2018 American Society of Civil Engineers.

**Author keywords:** Rainfall-runoff-inundation (RRI) model; Rainfall-runoff; Flood; Mekong River Basin.

## Introduction

Flooding is one of the major natural disasters that disrupt the prosperity and safety of human settlements (Jha et al. 2012). Flood risk is defined as the combination of actual flooding and vulnerable human systems, along with natural, human, social, economic, and environmental factors. Because flood risks are a damaging natural hazard, studies of flood phenomena and their consequences are useful for flood control and management along with risk reduction and improvement of resilience. Moreover, flood forecasting and early warning are essential for the evacuation of residents from areas of likely damage (Plate 2007). To understand flood phenomena, it is necessary to study the characteristics of hydrology, hydraulics,

geography, the sensitivity of human assets, and environmental economics (Eleutério 2012). Flood risk management is extremely complex, involving public and private interests while confronting social, economic, political, environmental, religious, and natural factors. It is very difficult to select comprehensive methods and models in order to implement flood damage estimations because different approaches may have different influences on estimation accuracy. One main challenge faced by researchers is the availability of data (Messner 2007).

A range of methods are available to estimate streamflow and flood extent in a catchment by using empirical and statistical techniques and rainfall-runoff models. Model selection is based on the purpose of the modeling, available time and money, hydrological elements, climatic and physiographic characteristics, data availability, model simplicity and ability, and the modeling expertise of the researchers. Rainfall-runoff models can be represented by five main characteristics in order of increasing complexity: a simple empirical method, a large-scale energy-water-balance equation, a conceptual model, a landscape daily hydrological model, and a distributed physically based hydrological model (Vaze et al. 2012). The commonly required data for rainfall-runoff models include climate data, topography, catchment areas, soil types, vegetation, water management structure, flow data, rainfall, and evapotranspiration. Model calibration is also an important process for optimizing or systematically adjusting the model's parameter values in order to best simulate streamflow. Model validation is the process of using calibrated parameters to simulate runoff over an independent period.

Flood inundation models are an essential tool for determining spatial hazards on flood maps. This provides predictions of flood hazards including flood extent and floodwater depth, which are used in the development of flood mitigation strategies as well as policy making. The data required for flood inundation models can be categorized

<sup>1</sup>Graduate Student, Dept. of Construction and Disaster Prevention Engineering, Kyungpook National Univ., 2559, Gyeongsang-daero, Sangju-si, Gyeongsangbuk-do 37224, Korea; Faculty of Hydrology and Water Resources Engineering, Institute of Technology of Cambodia, Russian Conf. Blvd., Phnom Penh 12156, Cambodia. ORCID: <https://orcid.org/0000-0003-4736-4568>

<sup>2</sup>Professor, Dept. of Construction and Disaster Prevention Engineering, Kyungpook National Univ., 2559, Gyeongsang-daero, Sangju-si, Gyeongsangbuk-do 37224, Korea (corresponding author). Email: [leegiha@knu.ac.kr](mailto:leegiha@knu.ac.kr)

<sup>3</sup>Researcher, International Water Resources Research Institute, Chungnam National Univ., 99 Daehak-ro, Yuseong-gu, Daejeon 34134, Korea.

<sup>4</sup>Lecturer and Senior Researcher, Faculty of Hydrology and Water Resources Engineering, Institute of Technology of Cambodia, Russian Conf. Blvd., Phnom Penh 12156, Cambodia.

<sup>5</sup>Professor, Dept. of Civil Engineering, Korea National Univ. of Transportation, Chungbuk 380-702, Korea.

Note. This manuscript was submitted on June 26, 2017; approved on December 12, 2017; published online on April 23, 2018. Discussion period open until September 23, 2018; separate discussions must be submitted for individual papers. This paper is part of the *Journal of Hydrologic Engineering*, © ASCE, ISSN 1084-0699.

into four main groups: (1) topographic data and floodplain delineation; (2) temporal flow rate data; (3) Manning's coefficients for river channel and slope; and (4) necessary data for calibration, validation, and assimilation (Smith et al. 2006). Existing flood inundation models can be distinguished according to the number of dimensions used to represent the spatial distribution of flow processes (Hunter et al. 2007), including zero-dimensional (0D) models, one-dimensional (1D) models, quasi two-dimensional (2D) models, 2D models, 1D–2D models, and three-dimensional (3D) mathematical descriptions of flow distribution.

The study on inundation modeling is still lacking in the large-scale basin, especially the Mekong River Basin. Most of the current inundation models are used to simulate in floodplains and are applied with a boundary condition of inflow from the upstream area (Sayama et al. 2015), particularly in the Mekong Basin (Dutta et al. 2007; Kazama et al. 2007). Generally, these boundary conditions were difficult to identify in cases of several inundations existing in a large-scale basin. Therefore, a fully distributed rainfall-runoff-inundation (RRI) model (Sayama et al. 2015) was employed. This RRI model is able to simultaneously simulate rainfall runoff and inundation in a large-scale river basin. The important feature of the RRI model is that it can interpolate missing satellite-based information (e.g., rainfall) in a flood inundation area and it calculates multiple basins in cases where the downstream floodplain can be affected by several rivers.

This paper aimed to (1) simulate the large-scale flooding with available grid precipitation data set and to investigate the characteristics of rainfall runoff and flood inundation processes during a large flood event in the Mekong River Basin using a 2D diffusive modeling approach, and (2) check the accuracy of the modeled inundation maps by comparing with the observed and satellite-based data.

## Methodology

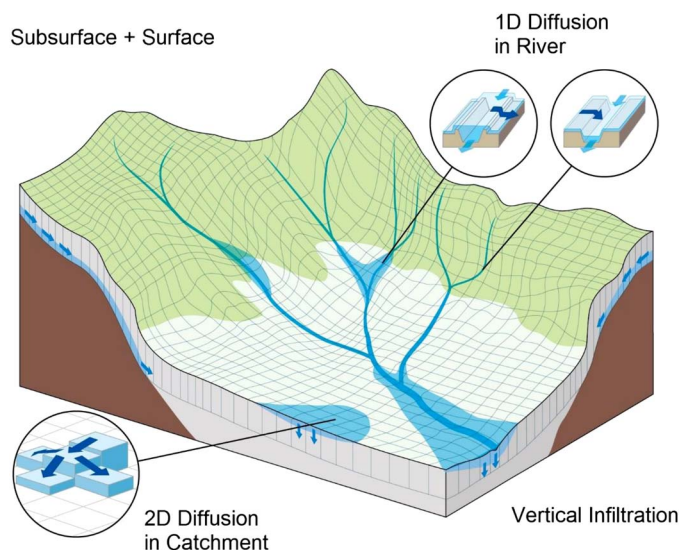
### Target Flood Event

The Mekong River system is one of the world's largest, with mean annual discharge of approximately 475 km<sup>3</sup> (MRC 2005), length of 4,909 km, and drainage area of 795,000 km<sup>2</sup> (MRC 2011). Its monthly discharge varies significantly between the wet season (June to November) and dry season (December to May) as a result of the southwest monsoon. Flooding is possible anywhere in the Lower Mekong River Basin, imposing significant economic and social damage; the average annual cost of flooding in this region is USD 60–70 million (MRC 2011). The major challenge for better flood risk management is to reduce the impacts and cost of flooding while preserving the benefits from annual flooding.

In 2000, flood conditions in the downstream reaches constituted an unusual scenario. In this case, the peak flood was average, but an unprecedented flood volume began 4–6 months earlier than usual, and floodwaters spread to areas not usually affected by flooding. The peak discharge and large volume of floodwater arrived during September; although the former was not significantly above the typical annual maximum, what made the 2000 flood so severe was the floodwater volume of 500 km<sup>3</sup>, matching a recurrence interval of 50 years (MRC 2007).

### RRI Model

The RRI model, a two-dimensional distributed hydrodynamic model, is able to simulate rainfall runoff and inundation processes simultaneously (Sayama et al. 2012). At the stream network cell level, the model supposes that both slope and river are located in the same grid. The model slope grid cells receive rainfall and



**Fig. 1.** RRI model. (Reprinted from Sayama et al. 2015, with permission.)

flow based on 2D diffusive wave equations, while the in-channel flow is calculated with 1D diffusive equations (Fig. 1). For better representation of real rainfall-runoff-inundation processes, the RRI model simulation considers lateral subsurface flow, vertical infiltration flow, and surface flow. The lateral subsurface flow is considered as saturated subsurface and surface flows, while the vertical infiltration is evaluated through the Green-Ampt method. The flow interaction between the river channel and slope is computed at each time step based on different overflowing formulas, depending on water-level and levee-height conditions (Sayama et al. 2012). The source codes of the RRI model were constructed with the Fortran 90 programming language.

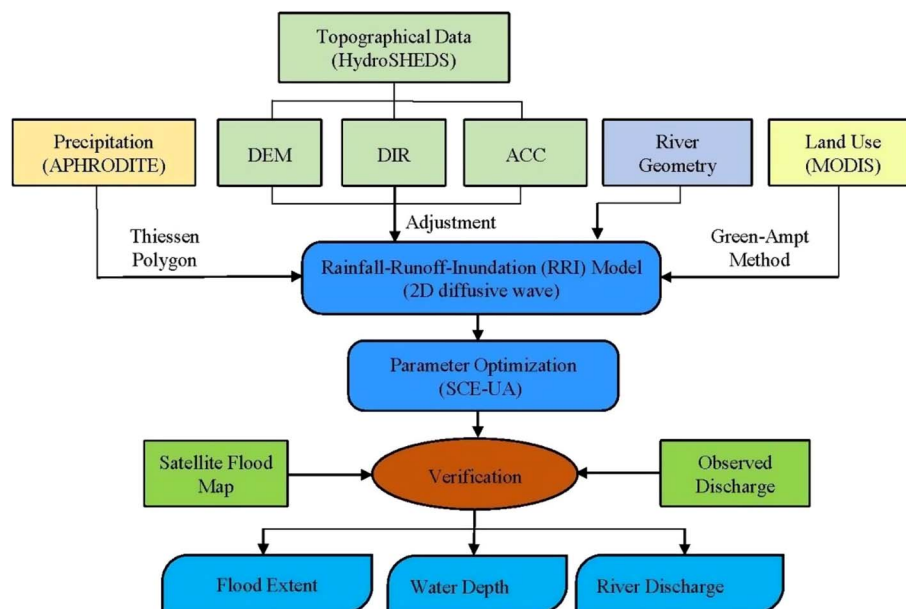
## Modeling Framework

The general framework of RRI model simulations is shown in Fig. 2. The required input data are precipitation data, geographic data [digital elevation model (DEM), flow direction, and flow accumulation], river geometry, and land use. The precipitation grid data were acquired from the APHRODITE product with 0.25° of spatial resolution. Topographic information was taken from the HydroSHEDS product, which provides a global data set of geographic information. The river's geometry was obtained from 12 observed cross sections along the main channel of the Mekong River. The land-use data were taken from the MODIS Land Cover Type product (MCD12Q1), in which each type of land use is classified to calculate vertical infiltration based on the Green-Ampt method. The RRI model was integrated with a global optimization tool [shuffled complex evolution (SCE-UA)] to calibrate the sensitive parameters. The output results of this model were inundation extent, flood water depth, and river discharge. The results were verified by using observed discharge at the main monitoring stations and observed flood extent derived from Landsat 7 satellite data.

## Input Data

### Topographic Data

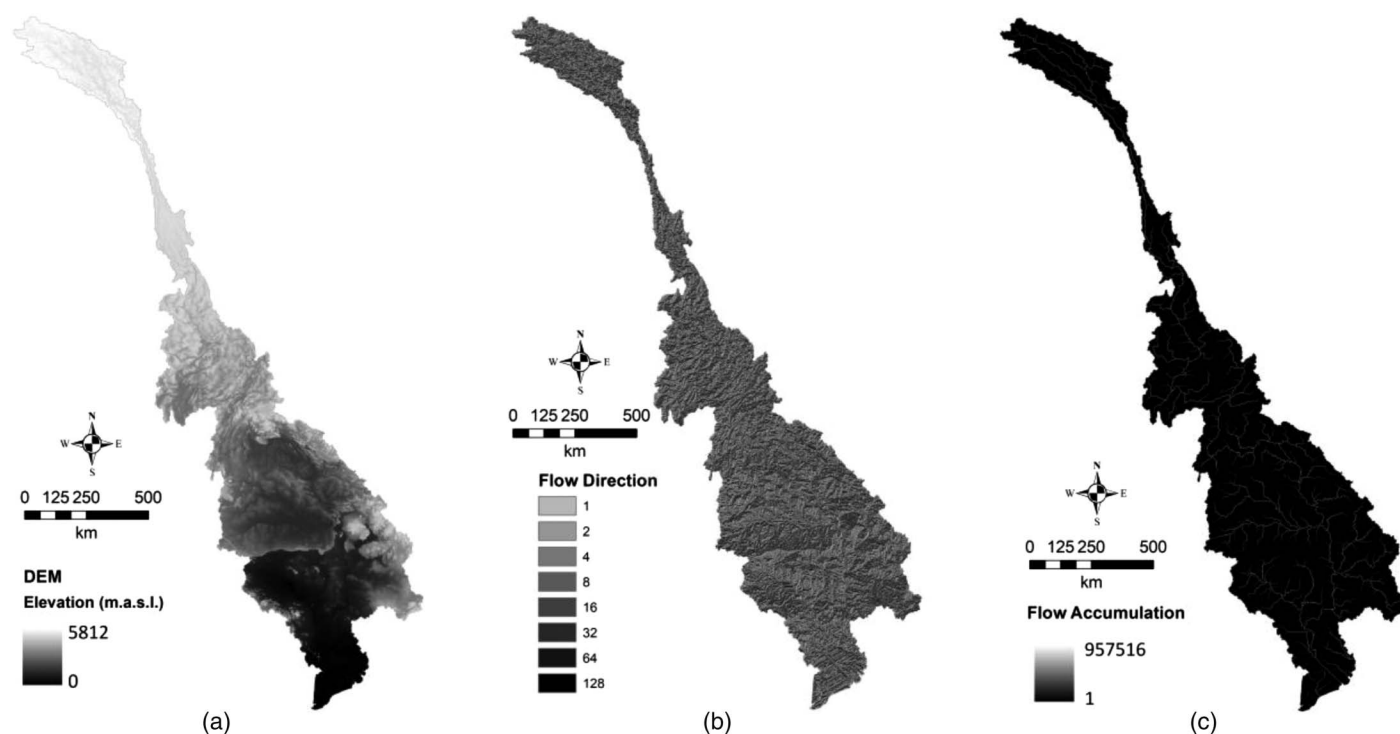
The topographic data used in this study were obtained from the HydroSHEDS project (Lehner et al. 2006), which was developed



**Fig. 2.** General framework of RRI model simulations.

by the Conservation Science Program of the World Wildlife Fund and provides global topographic information based on the Shuttle Radar Topography Mission (SRTM) (Farr and Kobrick 2000). HydroSHEDS DEMs are available in two product formats: void-filled DEMs and hydrologically conditioned DEMs. In the former, no-data voids are filled in and the main elevation inconsistencies have been removed. In the latter, DEMs are available for hydrological applications and are future conditioned to produce an actual river network. Fig. 3 shows topographic data (digital elevation model, flow direction, and flow accumulation) for the entire Mekong River

Basin. The original data set has a spatial resolution of 30 arcsec (approximately 0.9 km), but it was resampled to 90 arcsec (approximately 2.7 km) to reduce computational time due to the large study area. The number of grid cells is 596 columns  $\times$  1,000 rows over the entire Mekong River Basin. To prepare the topography data as an input for the RRI model, the DEM was adjusted in order to avoid the unrealistic hollows present in the original data. For instance, deep and narrow valleys in which the river flows may be blocked by surrounding topography, such that the simulated water depths and river discharges using the original DEM are unrealistic.



**Fig. 3.** Topographic data as inputs for the RRI model: (a) DEM; (b) flow direction; and (c) flow accumulation.



## Rainfall Data

Rainfall is the most important input data for the RRI model. The Mekong River Basin covers a very large watershed area, more than 795,000 km<sup>2</sup>, and the observed rainfall from rain gauges is quite limited. Therefore, rainfall data were obtained from the APHRODITE product managed by the Research Institute for Humanity and Nature (RIHN) and the Meteorological Research Institute of the Japan Meteorological Agency (MRI/JMA) (Yasutomi et al. 2011). These rainfall data cover 57 years from 1951 to 2007 and consist of a long-term daily gridded precipitation data set for Asia, collected and analyzed from rain gauge observations with 0.25° resolution (Yatagai et al. 2012). The Thiessen Polygon method was applied for missing grid points. The APHRODITE data set was validated by comparing with rain gauge data set at several areas during the period of 5 years from 2000 to 2004 (Fig. 4). The gap of uncertainty between the APHRODITE data set and the rain gauge data set corresponds with bias = −0.16, 0.16, and 0.19 and root-mean-squared error (RMSE) = 4.28, 7.65, and 7.07 mm/day in Chau Doc, Vietnam; Vientiane, Laos; and Luang Preahbang, Laos, respectively.

## Land Use

Land use has crucial impacts on components of the hydrological cycle such as evapotranspiration, infiltration, runoff, and erosion and sedimentation. Therefore, land-use effect is a critical

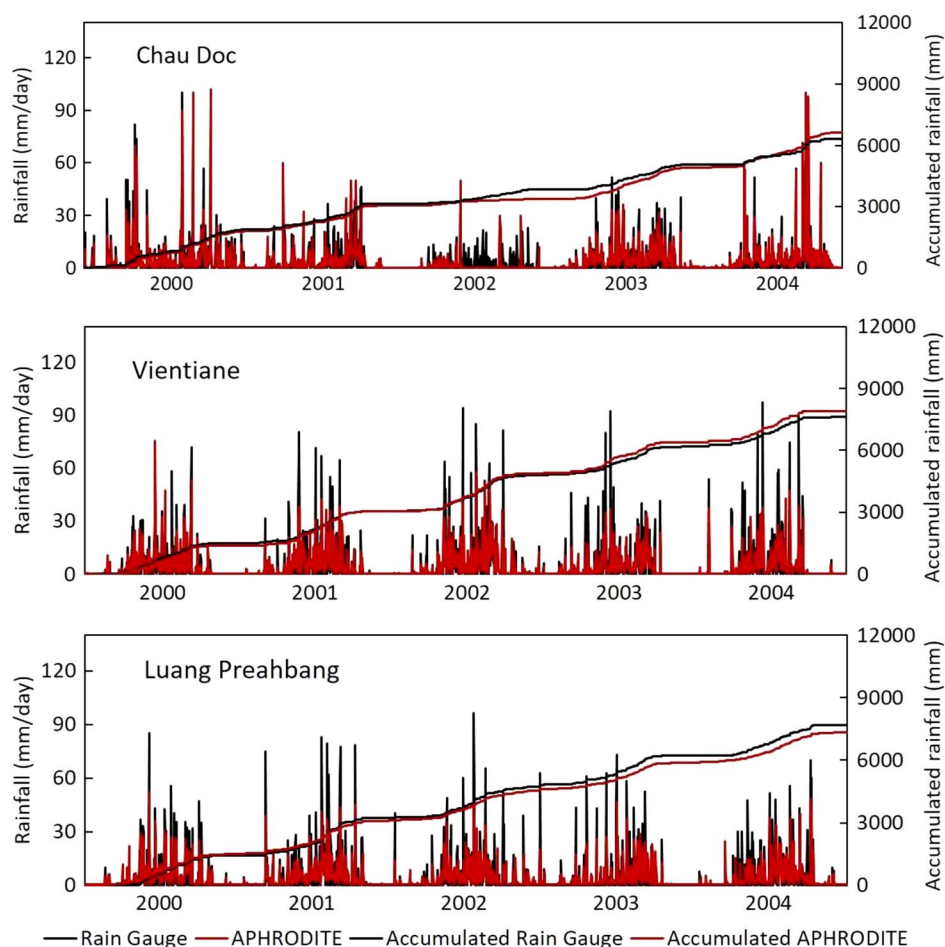
hydrological parameter when describing hydrological systems in a watershed; the RRI model considers land-use classification an important input parameter.

Land-use data were obtained from the MODIS Land Cover Type product (MCD12Q1) (Friedl et al. 2010) from 2000 to 2010. This product identifies 17 land-use types that are defined by the International Geosphere Biosphere Program (IGBP) including 11 natural vegetation classes, three developed and mosaicked land classes, and three nonvegetation classes [Fig. 5(a)]. However, these 17 types are too detailed to use as input data in the RRI model, which recommends reclassifying similar land-use types into the same type. As a result, three main land-use types are used in RRI model simulations [Fig. 5(b)]. The original data set had 0.5-km resolution, but it was resampled to the same resolution as the topographic data for use as input data in the model.

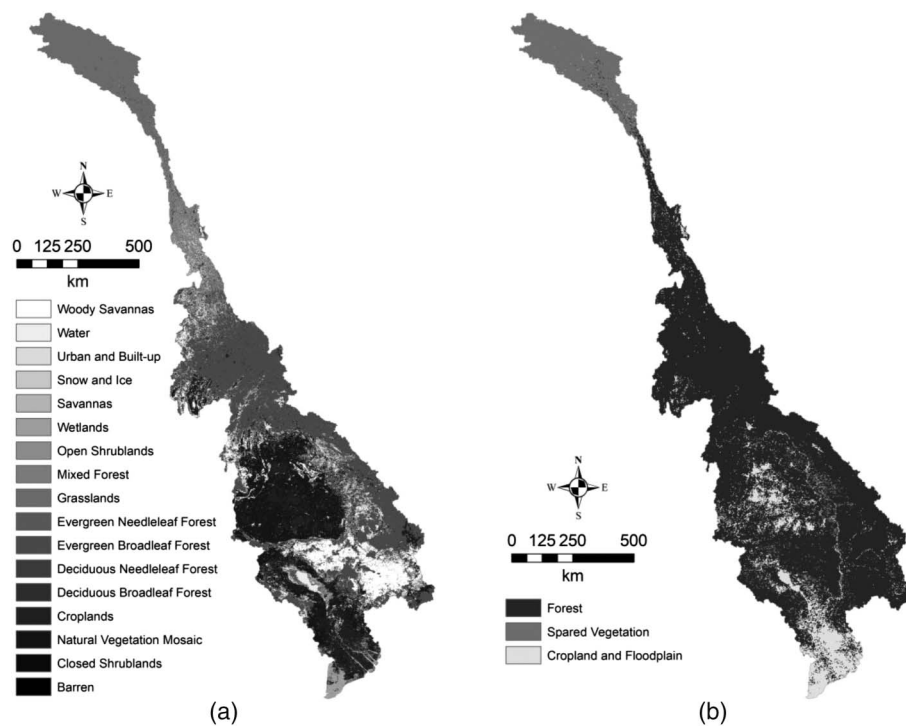
## River Geometry

Because there are no available surveyed data, the cross sections of the Mekong River were taken from the Mekong River Commission (MRC) website at 12 main monitoring stations (MRC n.d.). Therefore, the river depths  $D$  (m) and widths  $W$  (m) are approximated in a log-log plot in Fig. 6, resulting from the following equations:

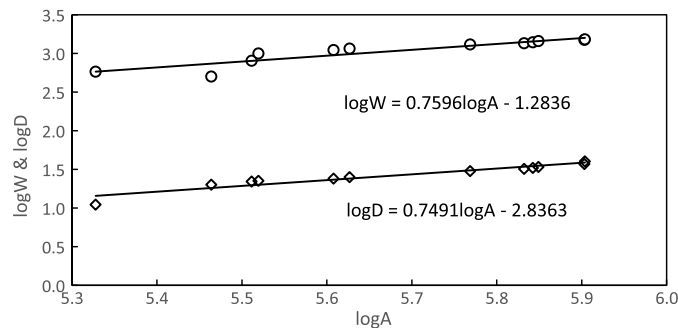
$$D = 0.0015A^{0.7491} \quad (1)$$



**Fig. 4.** Comparison between APHRODITE data sets for Chau Doc, Vietnam; Vientiane, Laos; and Luang Preahbang, Laos, stations during the period of 5 years from 2000 to 2004.



**Fig. 5.** Land-use classification in the Mekong River Basin: (a) original MODIS product with 17 land-use types; and (b) reclassified-land use types.



**Fig. 6.** Log-log plot of river width and river depth with contributing area.

$$W = 0.0520A^{0.7596} \quad (2)$$

where  $A$  = contributing area ( $\text{km}^2$ ). The relationship between contributing area and river depth [Eq. (1)] has uncertainty with bias = 0.03% and  $R^2 = 0.91$ , while contributing area and width [Eq. (2)] has bias = 0.03% and  $R^2 = 0.84$ .

## Optimization Tool

The SCE-UA method, developed at the University of Arizona, is an effective and efficient optimization technique for calibrating a nonlinear hydrologic simulation model. This computer-based automatic optimization algorithm has been widely used by numerous researchers (Gan and Biftu 1996; Kim et al. 2008; Lee et al. 2006, 2007; Lee and Kang 2015) and has been found to be an efficient and powerful method that is influenced by the choice of parameters. This approach follows three concepts: (1) the

combination of simplex procedures by applying a controlled random search approach; (2) competitive evolution; and (3) complex shuffling (Lee et al. 2006). The combination of these three components makes the SCE-UA effective, robust, and flexible (Duan et al. 1994). The automatic calibration aims to find the proper values of model parameters that maximize or minimize the value of the objective function.

Five parameters of the RRI model in the Mekong River Basin were found to be sensitive: Manning's roughness coefficients along the river channel, soil surface porosity, saturated hydraulic conductivity, unsaturated porosity, and the coefficient of unsaturated hydraulic conductivity. These five sensitive parameters ( $\theta$ ) were used in the SCE-UA calibration method to find the optimized values that are able to predict simulated discharge  $Q_t(\theta)$  close to the observed discharge  $Q_t^{obs}$ . Each parameter was a value classified as ranging from lower than the normal value to higher than the normal value.

The model performance indicators were used including the Nash-Sutcliffe efficiency (NSE), percent bias (PBIAS), and root-mean-square Error-observation standard deviation ratio (RSR), whose formulas are as follows:

$$NSE = 1 - \frac{\sum_1^n (Q_t^{obs} - Q_t(\theta))^2}{\sum_1^n (Q_t^{obs} - Q_t^{mean})^2} \quad (3)$$

$$PBIAS = \frac{\sum_1^n (Q_t^{obs} - Q_t(\theta)) \times 100}{\sum_1^n (Q_t^{obs})} \quad (4)$$

$$RSR = \frac{\sqrt{\sum_1^n (Q_t^{obs} - Q_t(\theta))^2}}{\sqrt{\sum_1^n (Q_t^{obs} - Q_t^{mean})^2}} \quad (5)$$

where  $Q_t^{obs}$  = observed stream flow value at time  $t$ ;  $Q_t(\theta)$  = simulated stream flow value at time  $t$  using parameter set  $\theta$ ; and

$n$  = number of available flow values. To evaluate the simulated and observed flood extent areas, success rate (SR) and modified success rate (MSR) were used as the following equations:

$$SR = \frac{\text{number of successful predictions as flood cells}}{\text{total number actual nonflood cells}} \times 100 \tag{6}$$

$$MSR = \left( 0.5 \times SR + 0.5 \times \frac{\text{number successful predictions as nonflood cells}}{\text{total number of actual nonflood cells}} \right) \times 100 \tag{7}$$

### Result and Discussion

The RRI model was applied to the Mekong River Basin to simulate the huge flood event in 2000. This model has the ability to predict river discharge, inundation extent, and flood water depth in the river

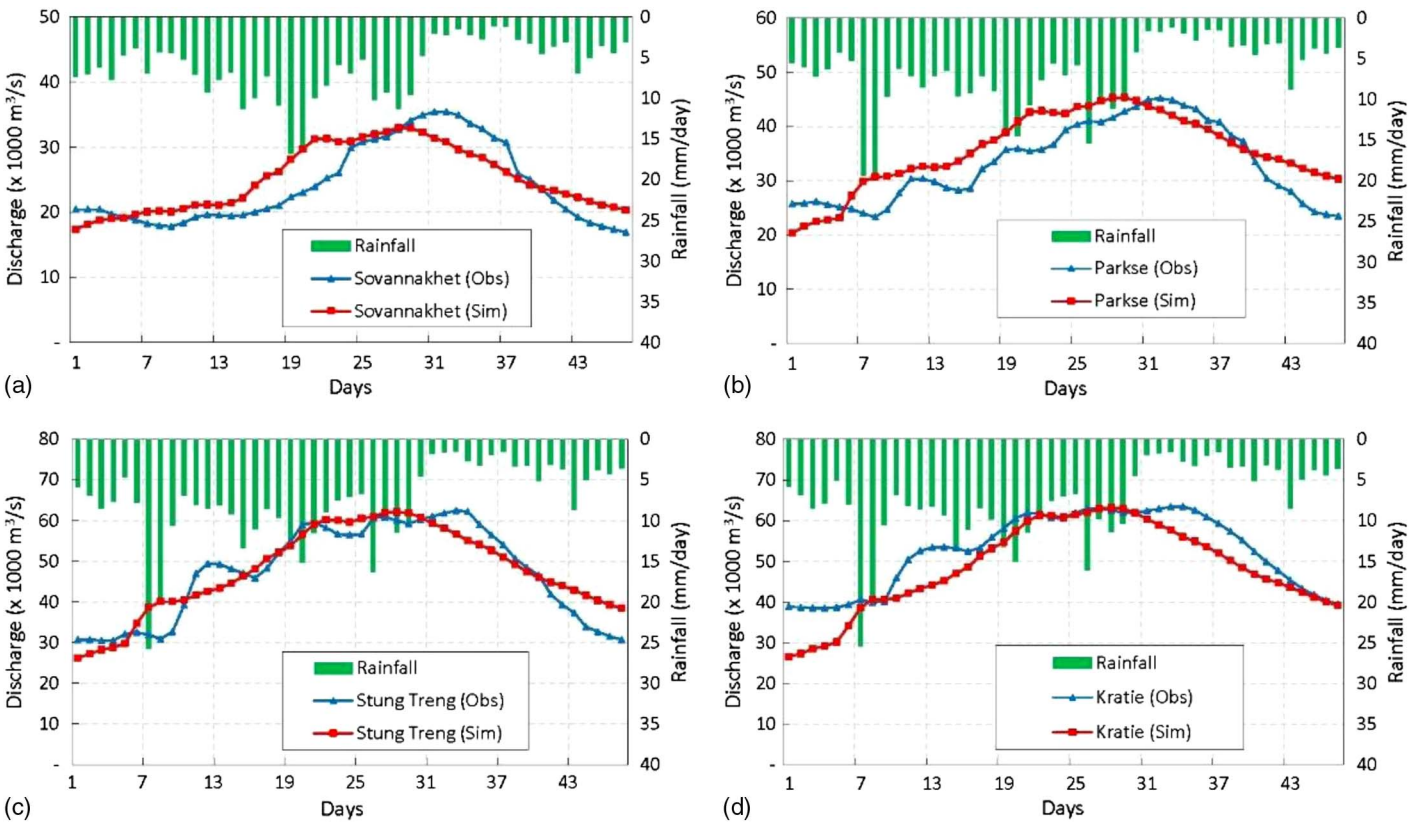
**Table 1.** Results of calibrated parameters from SCE-UA optimization method

Parameter	Symbol	Minimum value	Maximum value	Optimized values
Manning’s roughness coefficient for the river	$n_{river}$	0.005	0.04	0.010
Soil surface porosity	$\phi_a$	0.001	0.7	0.438
Saturated hydraulic conductivity	$k_a$	0.01	0.3	0.024
Unsaturated porosity	$\phi_m$	0.001	0.3	0.176
Coefficients of unsaturated hydraulic conductivity	$\beta = k_a/k_m$	5	15	12.139

and slope. The simulation was conducted during the annual peak flood period (47 days) from August 15, 2000, to September 30, 2000. Due to the fact that the Mekong River Basin is a very large basin, the simulation was also conducted for an extra period of 45 days prior to the main period for model warmup as well as for water to reach the downstream area. To calibrate the sensitive parameters, the number of simulations was set to 500 by integrating the RRI model with a global automatic optimization tool (SCE-UA). It took approximately 3 h per simulation (i.e., all 500 simulations took about 2 months) using Intel 64 Microsoft Visual Studio 2010 Intel Fortran Compiler in a computer [processor: Intel(R) Core(TM) i7-4790, China; CPU: 3.60 GHz; RAM: 8.00 GB]. Table 1 shows the calibrated parameters from the SCE-UA tool after 500 simulations. The optimized values of sensitive parameters were used as inputs for the RRI model, and the model was run afresh to investigate the results.

### Discharge

Fig. 7 compares the observed and simulated discharges at multiple locations along the mainstream of the Mekong River Basin. From



**Fig. 7.** Hydrograph of observed discharge and simulated discharge at (a) Savannakhet station; (b) Pakse station; (c) Stung Treng station; and (d) Kratie station.

**Table 2.** Result of performance indices of hydrograph

Index	Stung Treng	Pakse	Savannakhet	Kratie	Remark
NSE	0.86	0.63	0.69	0.63	NSE ranges from $-\infty$ to 1.0. NSE = 1 is perfect prediction (Nash and Sutcliffe 1970). PBIAS ranges from $\pm 100$ to 0%. PBIAS = 0% is the perfect prediction. The positive and negative values represent underestimation and overestimation bias, respectively (Gupta et al. 1999). RSR ranges from $+\infty$ to 0, where 0 indicates perfect model simulation (Singh et al. 2005).
PBIAS	-0.95%	-7.09%	-3.77%	-7.81%	
RSR	0.38	0.61	0.55	0.60	

the simulation results, the estimated peak discharge at Savannakhet Station was 32,986 m<sup>3</sup>/s on September 11, 2000, and the observed peak discharge was 35,411 m<sup>3</sup>/s on September 14, 2000. For Pakse Station, the simulated and observed peak discharge results were 45,338 m<sup>3</sup>/s on September 12, 2000, and 4,518 m<sup>3</sup>/s on September 15, 2000, respectively. At Stung Treng Station, the predicted and observed peak discharges were 62,093 m<sup>3</sup>/s on September 11, 2000, and 62,444 m<sup>3</sup>/s on September 16, 2000, respectively. Kratie Station is close to the downstream end of the basin. Here, the predicted and observed peak discharges were 63,135 m<sup>3</sup>/s on September 11, 2000, and 63,535 m<sup>3</sup>/s on September 17, 2000, respectively. In summary, the peak discharge results from the RRI model simulation were slightly lower than and happened several days before the observed peak discharges.

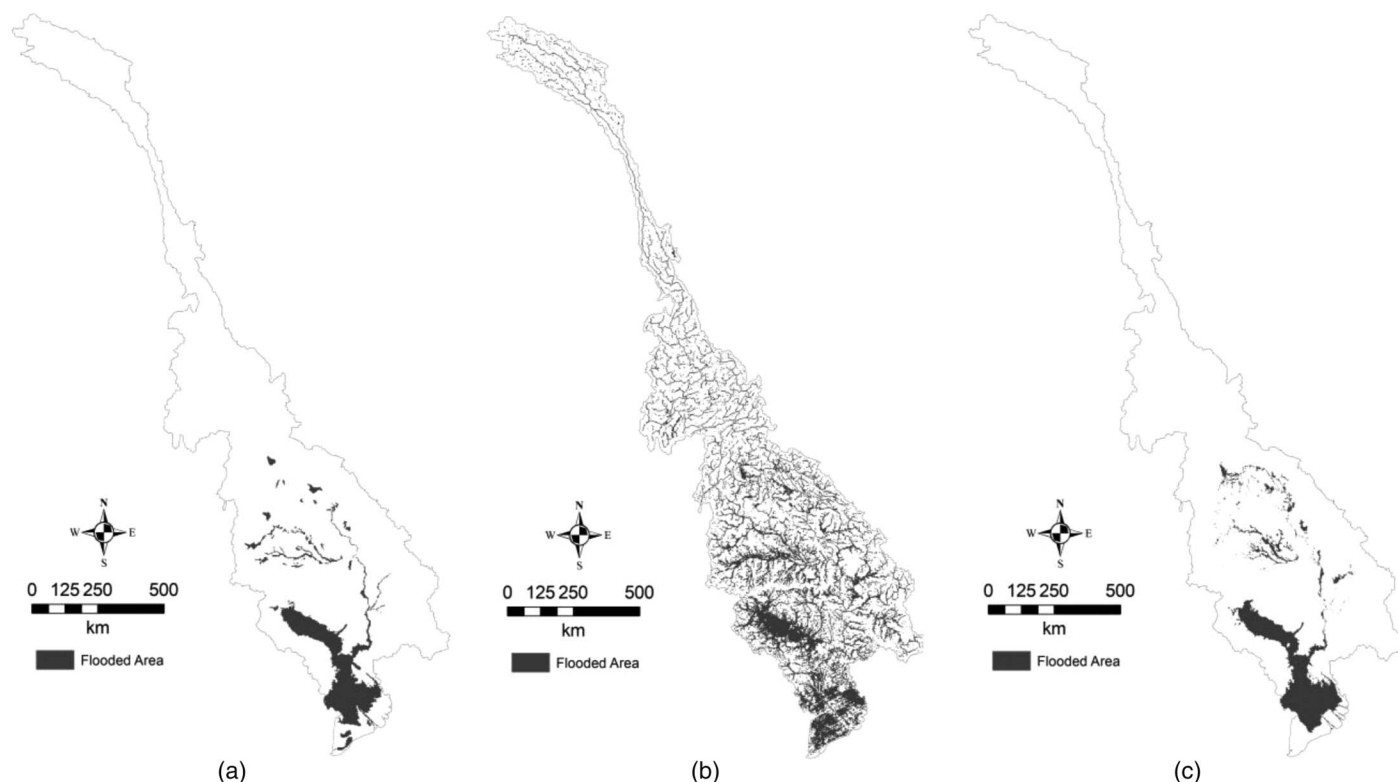
The drainage area of the Mekong River Basin is very large, approximately 795,000 km<sup>2</sup> (MRC 2011), and the water needs a period of time to accumulate from the upstream to reach the hydrological station. Therefore, the streamflow peak was usually later than the rainfall peak for several days (Fig. 7). The time difference between peak discharge and rainfall of the upper station

(i.e., Savannakhet and Pakse) was shorter than the downstream station (i.e., Stung Treng and Kratie).

The evaluation indexes of results indicated good agreement with observation data in both hydrograph and inundation areas (Table 2). At Savannakhet Station, the simulation predicted a good range with evaluation index NSE = 0.69, PBIAS = -3.77%, and RSR = 0.55. Similarly, the results at Pakse Station were NSE = 0.63, PBIAS = -7.09%, and RSR = 0.61. The accuracy of the model was especially good at Stung Treng Station, with NSE = 0.86, PBIAS = -0.95%, and RSR = 0.38, and NSE = 0.63, PBIAS = 7.81%, and RSR = 0.61 at Kratie Station. Because Stung Treng Station was determined a calibration station, the performance here was better than any other station.

### Flood Inundation

Fig. 8 shows the comparison between the inundation extent estimated by the RRI model and the observation of flood extent area. The observed inundated extent used in this study was derived from a Landsat 7 satellite image, captured during the annual peak flood



**Fig. 8.** Flood extent over the entire Mekong River Basin from (a) satellite Landsat 7; (b) results from the RRI model; and (c) MRC data.



**Table 3.** Result of performance indexes of flood inundation

Index	Inundation extent	Remark
Success rate	SR = 67.50% (Landsat 7) SR = 68.27% (MRC data)	SR and MSR range from 0 to 100%. SR and MSR = 100% means the model has the best performance.
Modified success rate	MSR = 74.53% (Landsat 7) MSR = 75.11% (MRC data)	

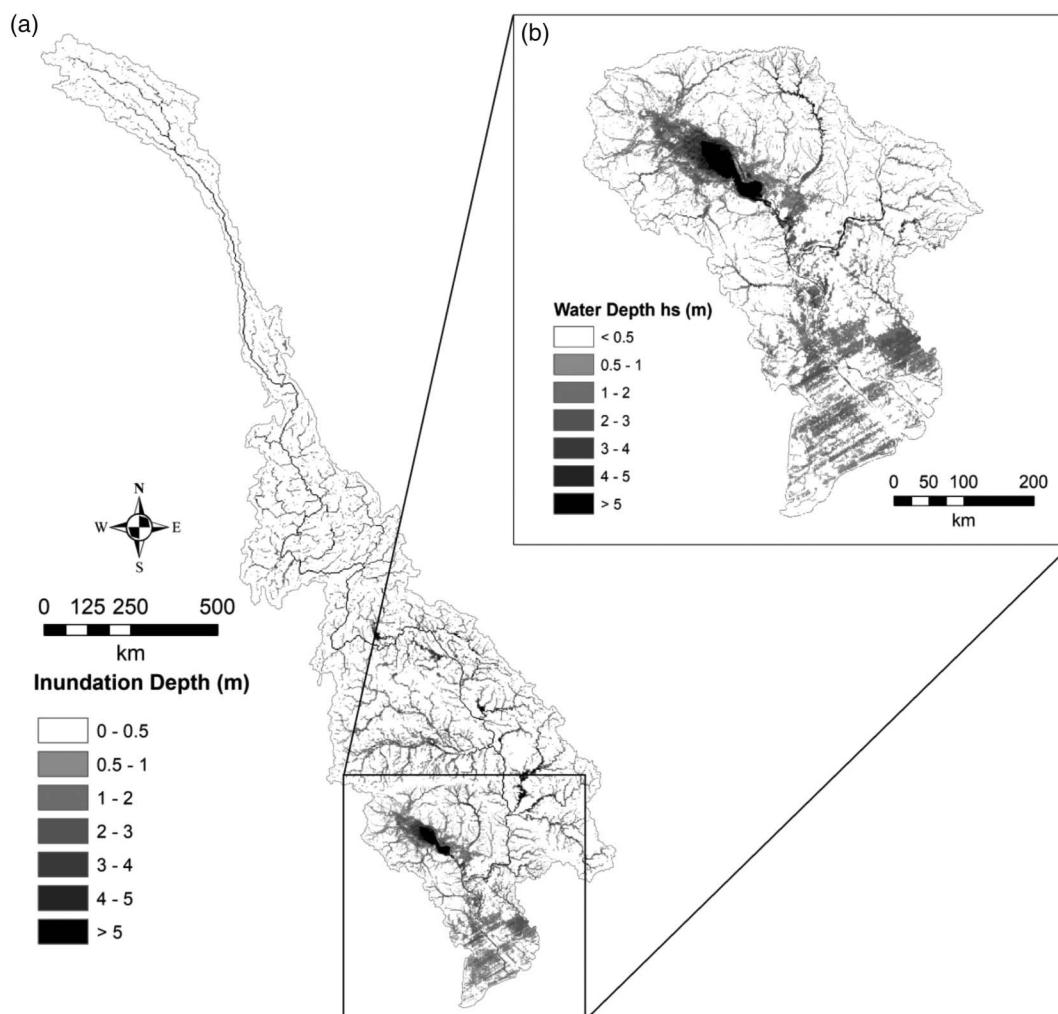
event in 2000 [Fig. 8(a)] by using digitized tool in ArcGIS and available data from MRC [Fig. 8(c)]. The simulation captures the pattern of flood inundation extent in the whole Mekong River Basin, especially in the lower part of the basin in the Tonle Sap floodplain and the Mekong Delta [Fig. 8(a)]. These parts of the basin are mainly agricultural areas with very low elevation. The evaluation index of spatial extent shows SR = 67.50% and MSR = 74.53% compared with the satellite Landsat 7, and SR = 68.27% and MSR = 75.11% compared with MRC data.

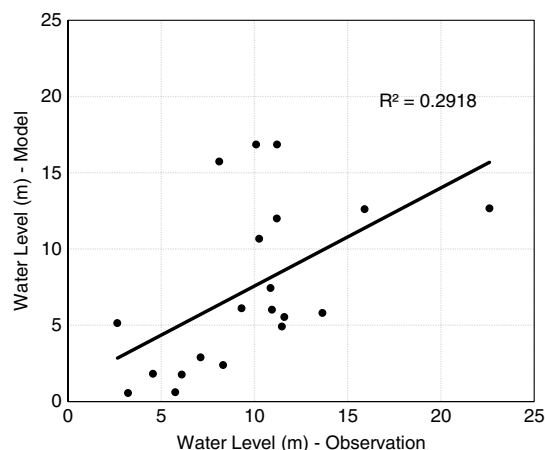
Table 3 gives these evaluating indexes of model performance, their values, and a brief explanation. The results indicated that the predicted flood extent was underestimated compared with satellite observation images; this could have been caused by the

uncertainty of the input data. The relatively low SR and MSR may be associated with the very-large-scale application of the model in the Mekong River Basin. Generally, remote sensing methods may judge areas as flooded even with shallow water depths (e.g., paddy fields). In addition, the areas having water depth greater than 0.5 m were considered as flood areas, and areas having water depth less than 0.5 m were classified as nonflood areas. Previous applications of the RRI model (Sayama et al. 2012, 2015) also predicted similar underestimations of flood inundation extent. More importantly, the effect of the coarse resolution of the DEM might influence the accuracy of the flood inundation extent. Fig. 9 illustrates the flood inundation depth over the entire Mekong River Basin [Fig. 9(a)] and the Lower Mekong Basin [Fig. 9(b)] resulting from the RRI model.

### Water Level

Fig. 10 presents the comparison between the observed and simulated peak inundation depths. Along the Mekong River's main-stream and inside the Tonle Sap floodplain, 20 designated locations were investigated. The peak water level shown in Fig. 10 clearly indicates the underestimation of the model simulation. Among the 20 locations, observed water depths were deeper than simulation results in 14 locations, while the other six locations were shallower. The correlation between simulation and observation was

**Fig. 9.** Flood inundation depth over (a) the entire Mekong River Basin; and (b) the Lower Mekong River Basin.



**Fig. 10.** Observed and simulated peak water levels in the Mekong River and the areas around the Tonle Sap floodplain.

$R^2 = 0.29$ . This underestimation effect could be caused by the coarse resolution of the topographic grid cells, the assumption of the cross section of the river channel, and uncertainty of inputs. On the other hand, the floodwaters in the simulation moved downstream more quickly and smoothly.

## Conclusion

In this study, the characteristics of a huge flood event in 2000 in the Mekong River Basin were investigated by applying a coupling rainfall-runoff and inundation model. The results indicated good agreement when comparing the observation data in both hydrograph and inundation extent. The peak discharge resulting from the RRI model was slightly lower than the observed discharge and occurred several days earlier.

The simulation identified the pattern of flood inundation in the entire Mekong River Basin, especially the lower part in the Tonle Sap floodplain in Cambodia and the Mekong Delta in Vietnam. The results indicated that the model underestimated the actual flood, which could have been caused by uncertainties in the input data, river geometry parameters, the large basin, and the coarse resolution of topographic data. In addition, remote sensing images might also contain errors in detecting flooded areas.

However, the RRI model was successfully applied to investigate and simulate the large 2000 flood in the Mekong River Basin. These results can serve as a principal source of information for governments, nongovernmental organizations (NGOs), agencies, and other related stakeholders and policymakers with regards to decision making, early warning, and other mitigation strategies on flood hazards in the Mekong River Basin. The results could be improved if the accuracy and quality of data can be increased, for example, if ground-based rain gauge data for precipitation became available for the entire study area. Ground observations such as hydrological, climate, soil, and topographical data, as well as flood damage of historical events, should be well recorded as a useful source of data for future studies.

## Acknowledgments

This research is supported by the Korean Ministry of Environment (MOE) as GAIA Program-2014000540005. The authors would

like to acknowledge the Mekong River Commission for providing hydrological data in this study.

## References

- Duan, Q., S. Sorooshian, and V. K. Gupta. 1994. "Optimal use of the SCE-UA global optimization method for calibrating watershed models." *J. Hydrol.* 158 (3–4): 265–284. [https://doi.org/10.1016/0022-1694\(94\)90057-4](https://doi.org/10.1016/0022-1694(94)90057-4).
- Dutta, D., J. Alam, K. Umeda, M. Hayashi, and S. Hironaka. 2007. "A two-dimensional hydrodynamic model for flood inundation simulation: A case study in the lower Mekong river basin." *Hydrol. Processes* 21 (9): 1223–1237. <https://doi.org/10.1002/hyp.6682>.
- Eleutério, J. 2012. "Flood risk analysis: impact of uncertainty in hazard modelling and vulnerability assessments on damage estimations." Ph.D. thesis, National School for Water and Environmental Engineering of Strasbourg, Univ. of Strasbourg.
- Farr, T. G., and M. Kobrick. 2000. "Shuttle radar topography mission produces a wealth of data." *EOS Trans. Am. Geophys. Union* 81 (48): 583–585. <https://doi.org/10.1029/EO081i048p00583>.
- Friedl, M. A., D. Sulla-Menashe, B. Tan, A. Schneider, N. Ramankutty, A. Sibley, and X. Huang. 2010. "MODIS Collection 5 global land cover: Algorithm refinements and characterization of new datasets." *Remote Sens. Environ.* 114 (1): 168–182. <https://doi.org/10.1016/j.rse.2009.08.016>.
- Gan, T. Y., and G. F. Biftu. 1996. "Automatic calibration of conceptual rainfall-runoff models: Optimization algorithms, catchment conditions, and model structure." *Water Resour. Res.* 32 (12): 3513–3524. <https://doi.org/10.1029/95WR02195>.
- Gupta, H. V., S. Sorooshian, and P. O. Yapo. 1999. "Status of automatic calibration for hydrologic models: Comparison with multilevel expert calibration." *J. Hydrol. Eng.* 4 (2): 135–143. [https://doi.org/10.1061/\(ASCE\)1084-0699\(1999\)4:2\(135\)](https://doi.org/10.1061/(ASCE)1084-0699(1999)4:2(135)).
- Hunter, N. M., P. D. Bates, M. S. Horritt, and M. D. Wilson. 2007. "Simple spatially-distributed models for predicting flood inundation: A review." *Geomorphology* 90 (3–4): 208–225. <https://doi.org/10.1016/j.geomorph.2006.10.021>.
- Jha, A. K., R. Bloch, and J. Lamond. 2012. *Cities and flooding: A guide to integrated urban flood risk management for the 21st century*. Washington, DC: World Bank Publications.
- Kazama, S., T. Hagiwara, P. Ranjan, and M. Sawamoto. 2007. "Evaluation of groundwater resources in wide inundation areas of the Mekong River basin." *J. Hydrol.* 340 (3): 233–243. <https://doi.org/10.1016/j.jhydrol.2007.04.017>.
- Kim, S., Y. Tachikawa, G. Lee, and K. Takara. 2008. "Prediction of the largest ever flood: Case study on Typhoon Rusa in 2002 at the Gamcheon Basin, Korea." *Proc. Hydraul. Eng.* 52: 67–72. <https://doi.org/10.2208/prohe.52.67>.
- Lee, G., Y. Tachikawa, and K. Takara. 2006. *Analysis of hydrologic model parameter characteristics using automatic global optimization method*, 67–80. Kyoto, Japan: Annals of Disaster Prevention Research Institute, Kyoto Univ.
- Lee, G., Y. Tachikawa, and K. Takara. 2007. "Identification of model structural stability through comparison of hydrologic models." *Proc. Hydraul. Eng.* 51: 49–54. <https://doi.org/10.2208/prohe.52.67>.
- Lee, S., and T. Kang. 2015. "Analysis of constrained optimization problems by the SCE-UA with an adaptive penalty function." *J. Comput. Civ. Eng.* 30 (3): 04015035. [https://doi.org/10.1061/\(ASCE\)CP.1943-5487.0000493](https://doi.org/10.1061/(ASCE)CP.1943-5487.0000493).
- Lehner, B., K. Verdin, and A. Jarvis. 2006. *HydroSHEDS technical documentation, version 1.0*. Washington, DC: World Wildlife Fund.
- Messner, F. 2007. *Evaluating flood damages: Guidance and recommendations on principles and methods*. Leipzig, Germany: Helmholtz Umweltforschungszentrum (UFZ).
- MRC (Mekong River Commission). n.d. *Overview*. Vientiane, Laos: MRC. Accessed October 15, 2016. <http://ffw.mrcmekong.org/overview.htm>.
- MRC (Mekong River Commission). 2005. *Overview of the hydrology of the Mekong basin*. Vientiane, Laos: MRC.

- MRC (Mekong River Commission). 2007. *Annual Mekong flood report 2006*. Vientiane, Laos: MRC.
- MRC (Mekong River Commission). 2011. *Planning atlas of the lower Mekong river basin*. Vientiane, Laos: MRC.
- Nash, J. E., and J. V. Sutcliffe. 1970. "River flow forecasting through conceptual models. Part I: A discussion of principles." *J. Hydrol.* 10 (3): 282–290. [https://doi.org/10.1016/0022-1694\(70\)90255-6](https://doi.org/10.1016/0022-1694(70)90255-6).
- Plate, E. J. 2007. "Early warning and flood forecasting for large rivers with the lower Mekong as example." *J. Hydro-environ. Res.* 1 (2): 80–94. <https://doi.org/10.1016/j.jher.2007.10.002>.
- Sayama, T., G. Ozawa, T. Kawakami, S. Nabesaka, and K. Fukami. 2012. "Rainfall-runoff-inundation analysis of the 2010 Pakistan flood in the Kabul River basin." *Hydrol. Sci. J.* 57 (2): 298–312. <https://doi.org/10.1080/02626667.2011.644245>.
- Sayama, T., Y. Tatebe, Y. Iwami, and S. Tanaka. 2015. "Hydrologic sensitivity of flood runoff and inundation: 2011 Thailand floods in the Chao Phraya River basin." *Natl. Hazards Earth Syst. Sci.* 2 (7): 7027–7059. <https://doi.org/10.5194/nhess-15-1617-2015>.
- Singh, J., H. V. Knapp, J. Arnold, and M. Demissie. 2005. "Hydrological modeling of the Iroquois river watershed using HSPF and SWAT1." *J. Am. Water Resour. Assoc.* 41 (2): 343–360.
- Smith, M. J., E. P. Edwards, G. Priestnall, and P. Bates. 2006. *Exploitation of new data types to create digital surface models for flood inundation modeling*. FRMRC Research Rep. UR3. UK: Flood Risk Management Research Consortium.
- Vaze, J., P. Jordan, R. Beecham, A. Frost, and G. Summerell. 2012. *Guidelines for rainfall-runoff modelling: Towards best practice model application*. Bruce, Australia: Water Cooperative Research Centre.
- Yasutomi, N., A. Hamada, and A. Yatagai. 2011. "Development of a long-term daily gridded temperature dataset and its application to rain/snow discrimination of daily precipitation." *Global Environ. Res.* 15 (2): 165–172.
- Yatagai, A., K. Kamiguchi, O. Arakawa, A. Hamada, N. Yasutomi, and A. Kitoh. 2012. "APHRODITE: Constructing a long-term daily gridded precipitation dataset for Asia based on a dense network of rain gauges." *Am. Meteorol. Soc.* 93 (9): 1401–1415. <https://doi.org/10.1175/BAMS-D-11-00122.1>.